Title
Near-surface remote sensing of canopy architecture and land-atmosphere interactions in an oak savanna ecosystem

Permalink
https://escholarship.org/uc/item/51p4x4d7

Author
Ryu, Youngryel

Publication Date
2010

Peer reviewed|Thesis/dissertation
Near-surface remote sensing of canopy architecture and land-atmosphere interactions in an oak savanna ecosystem

by

Youngryel Ryu

A dissertation submitted in partial satisfaction of the requirements for the degree of Doctor of Philosophy in Environmental Science, Policy and Management in the Graduate Division of the University of California, Berkeley

Committee in charge:
Professor Dennis D. Baldocchi, Chair
Professor Todd E. Dawson
Professor Peng Gong
Professor John C.H. Chiang

Spring 2010
Near-surface remote sensing of canopy architecture and land-atmosphere interactions in an oak savanna ecosystem

Copyright 2010

by

Youngryel Ryu
Abstract

Near-surface remote sensing of canopy architecture and land-atmosphere interactions in an oak-savanna ecosystem

by

Youngryel Ryu

Doctor of Philosophy in Environmental Science, Policy and Management
University of California, Berkeley
Professor Dennis Baldocchi, Chair

Canopy architecture plays fundamental roles in the land-atmosphere interactions, yet quantification of canopy architecture using optical sensors in an open canopy remains a challenge. Savannas are spatially heterogeneous, open ecosystems, thus efforts to quantify canopy structure with methods developed for homogeneous, closed canopies are prone to failure. I employed a multi-model and multi-instrument approach to quantify leaf area index in an oak savanna ecosystem of California. I found that the effective area index should be calculated by taking the logarithm of average gap fraction. Contrary to boreal and temperate forests, the savanna ecosystem was highly clumped at the ecosystem scale (clumping index=0.49). Thus quantification of clumping effects at the ecosystem scale, which has been overlooked in most leaf area index products, is crucial to obtain the correct leaf area index.

To investigate how evaporation in the annual grassland of the savanna ecosystem is modulated by biological/environmental factors, I investigated the 6 year evaporation data measured with an eddy covariance system. The annual evaporation ranged between 266 mm to 391 mm despite a two-fold range in precipitation. I found that the pronounced energy-limited and water-limited periods occurred within the same year. In the water-limited period, monthly integrated evaporation scaled negatively with solar radiation and was restrained by precipitation. In the energy-limited period, on the other hand, the majority of evaporation scaled positively with solar radiation and was confined by potential evaporation. Evaporation was most sensitive to the availability of soil moisture during the transition to the senescence period rather than the onset of the greenness period, causing annual evaporation to be strongly modulated by the length of growing season.

To bridge canopy structure, function and metabolism, I tested the use of light emitting diodes (LEDs) to monitor the vegetation reflectance in narrow spectral bands. LEDs are appealing because they are inexpensive, small and reliable light sources that used in reverse mode, can measure spectrally selective radiation. To test the efficacy of this approach, I measured the spectral reflectance with LEDs in red and near-infrared wavebands, which are used to calculate the normalized difference vegetation index over the grassland over 3.5 years. The LED-spectrometer captured daily to inter-annual variation of the spectral reflectance at the two bands.
with reliable and stable performance. The spectral reflectance in the two bands and NDVI proved to be useful to identify the leaf-on and leaf-off dates (mean bias errors of 5.3 and 4.2 days, respectively) and to estimate the canopy photosynthesis ($r^2=0.91$). I suggest that this novel instrument can monitor other structural and functional (e.g. leaf area index, leaf nitrogen) variables by employing the LEDs that have other specific wavelengths bands. Considering that off-the-shelf LEDs cover a wide range of wavebands from the ultraviolet to near-infrared regions, I believe that the research community could explore a range of similar instruments across a range of bands for a variety of ecological applications.

The regular monitoring of evaporation from satellites has been limited because of discontinuous temporal coverage. Here, I found a strong linear relationship between mean hourly $\lambda E$ (i.e., 1000-1100hh; 1100-1200hh; 1200-1300hh; 1300-1400hh) and 8-day means of $\lambda E$ at 26 eddy covariance flux towers across seven plant functional types from boreal to tropical climatic zones. Hourly time steps of evaporation were selected to correspond with potential overpass times of the MODIS Terra and Aqua satellites. The mean slope of the linear relationship between mean hourly means of evaporation and 8-day, 24-h evaporation means showed no significant differences among sites and for each of the four mid-day hours. The results suggest a factor of 0.370 (95% CI: 0.354, 0.385) can be used to temporally upscale instantaneous evaporation measurements averaged over 8-day periods to an 8-day mean evaporation.
To my father
Inho You (1943-2009)
who showed me how to live and how to love
Table of Contents

1. Chapter 1: Introduction........................................................................................................... 1
2. Chapter 2: How to quantify tree leaf area index in an open savanna ecosystem..... 3
   2.1. Introduction.................................................................................................................. 3
   2.2. Theoretical background............................................................................................... 5
       2.2.1. Leaf projection function and leaf inclination distribution function .......... 5
       2.2.2. Gap fraction and leaf area index ................................................................. 6
   2.3. Methods....................................................................................................................... 7
       2.3.1. Site description................................................................................................. 7
       2.3.2. Sampling design, measurements, and data processing................................. 8
           2.3.2.1. Sampling design ................................................................................. 8
           2.3.2.2. Leaf inclination angle ....................................................................... 9
           2.3.2.3. LAI-2000 ......................................................................................... 10
           2.3.2.4. Tracing Radiation and Architecture of Canopies.......................... 10
           2.3.2.5. Digital hemispherical photography .................................................. 10
           2.3.2.6. Digital cover photography ................................................................. 11
           2.3.2.7. Traversing radiometer system ........................................................... 11
           2.3.2.8. Allometry ........................................................................................... 12
           2.3.2.9. Litterfall ............................................................................................. 12
           2.3.3. Gap fraction models ..................................................................................... 12
           2.3.4. Uncertainty and statistical analyses ............................................................. 13
   2.4. Results.......................................................................................................................... 14
       2.4.1. Leaf inclination angle distribution function and leaf projection function... 14
       2.4.2. Gap fraction .................................................................................................... 15
       2.4.3. Element clumping index .............................................................................. 18
       2.4.4. Woody area index ........................................................................................ 20
       2.4.5. Leaf area index ............................................................................................. 20
       2.4.6. Minimum sample size and plot size ............................................................... 21
   2.5. Discussion...................................................................................................................... 22
       2.5.1. What are the strengths and weaknesses of multiple methods to assess \( L \) in heterogeneous, open canopies? ................................................................. 23
       2.5.2. How to estimate spatially representative clumping index in savannas? ...... 26
       2.5.3. Angular dependence of element clumping index ........................................ 27
       2.5.4. Influence of gaps between crowns on total gap fraction............................. 28
   2.6. Summary and Conclusions............................................................................................ 28
3. Chapter 3: On the correct estimation of effective leaf area index................................. 30
   3.1. Introduction.................................................................................................................. 30
   3.2. Methods and Materials............................................................................................... 31
       3.2.1. Theory ........................................................................................................... 31
       3.2.2. Forest gap fraction model ........................................................................... 32
       3.2.3. Data .............................................................................................................. 33
       3.2.4. Spatial scaling of apparent clumping index ............................................... 34
   3.3. Results and Discussion............................................................................................... 34
       3.3.1. Theoretically consistent \( L_e \) .................................................................... 34
       3.3.2. The effect of canopy structure on apparent clumping index ...................... 36
3.3.3. Clumping effects accounted for by the LAI-2000 instrument...................... 38
3.3.4. Implications of apparent clumping index to vegetation clumping study...... 44
  3.3.4.1. Constraint on true clumping index................................................... 44
  3.3.4.2. Spatial scaling of clumping index.................................................... 45
  3.3.4.3. Seasonal variation of clumping index.............................................. 46
3.4. Summary and Conclusions........................................................................ 49
4. Chapter 4: Interannual variability of evaporation and energy exchange over an annual grassland................................................................. 50
  4.1. Introduction.................................................................................................. 50
  4.2. Methods...................................................................................................... 53
    4.2.1. Sites description................................................................................... 53
    4.2.2. Data acquisition.................................................................................. 53
    4.2.3. Gap filling, assessing uncertainty, and data processing...................... 54
    4.2.4. Calculations of bulk parameters....................................................... 55
  4.3. Results........................................................................................................ 57
    4.3.1. General weather conditions and phenology........................................ 57
    4.3.2. PAR albedo........................................................................................ 59
    4.3.3. Radiation and energy flux densities.................................................... 61
    4.3.4. Bulk parameters.................................................................................. 64
  4.4. Discussion................................................................................................... 65
    4.4.1. Comparison of energy fluxes with other studies.................................. 65
    4.4.2. Constraints on $E$............................................................................... 66
      4.4.2.1. Water and energy............................................................................ 66
      4.4.2.2. Physiological control via surface conductance............................... 69
      4.4.2.3. Main determinant on annual ET amount: Growing season length.. 70
    4.4.3. Application of long-term flux measurements to testing a plant functional type scheme................................................................. 71
  4.5. Summary and Conclusions......................................................................... 73
5. Chapter 5: Testing the performance of a novel spectral reflectance sensor, built with light emitting diodes (LEDs), to monitor ecosystem metabolism, structure and function........................................................................... 75
  5.1. Introduction.................................................................................................. 75
  5.2. Methods...................................................................................................... 76
    5.2.1. Study site............................................................................................ 76
    5.2.2. LED-spectrometer............................................................................... 76
      5.2.2.1. Development................................................................................... 76
      5.2.2.2. Calibration using hyperspectral reflectance measurements........... 78
    5.2.3. Ancillary measurements...................................................................... 79
  5.3. Results and Discussion............................................................................... 80
    5.3.1. Effects of the solar zenith angles on the red, NIR reflectance and NDVI of the LED-spectrometer................................................................. 80
    5.3.2. Seasonal and interannual variation of spectral reflectance.................. 82
    5.3.3. Extracting key phenological events of grass community.................... 84
    5.3.4. Investigating seasonality of canopy photosynthesis............................ 85
    5.3.5. Exploring optimal LED wavelengths for improved monitoring of ecosystem structure and metabolism............................................................... 87
List of Figures

Figure 2. 1. Plot design and a schematic diagram of protocol used to measure leaf inclination angle ........................................................................................................................................ 8

Figure 2. 2. Histogram of leaf inclination angle and leaf projection function against view zenith angle ........................................................................................................................................ 15

Figure 2. 3. Gap fraction comparison among LAI-2000, DHP, TRAC and DCP sensors with two gap fraction models using Nilson 1999 and Kobayashi and Iwabuchi 2008. Comparison between gap fraction from direct measurement and gap fraction calculated from accumulated gap fraction function .......................................................................................................................... 17

Figure 2. 4. Element clumping index with solar zenith angle measured from a traversing radiometer system, TRAC sensor, Nilson 1999, Kobayashi and Iwabuchi 2008, inversion calculation, DCP ........................................................................................................................................ 19

Figure 2. 5. Effective leaf area index comparison among LAI-2000, DCP, DHP, TRAC, TRS and Nilson (1999). Leaf area index comparison among litterfall, allometry, DHP, DCP, TRAC and RTS ........................................................................................................................................ 21

Figure 2. 6. Coefficient of variation for mean gap fraction at each view zenith angles in LAI-2000 with sampling numbers. Coefficient of variation of effective leaf area index measured from LAI-2000 with window size within the 300×300 m area ........................................................................................................................................ 22

Figure 2. 7. Subset of an image of Digital Cover Photograph and an image of Digital Hemispheric Photograph ........................................................................................................................................ 25

Figure 3. 1. A conceptual diagram to calculate effective leaf area index ........................................................................................................................................ 35

Figure 3. 2. The relation among canopy cover, variance of gap fraction, crown shape, non-linear correction term, normalized non-linear correction term and apparent clumping index ........................................................................................................................................ 37

Figure 3. 3. Comparison of element clumping index between LAI-2000 derived method and independent estimate from literature ........................................................................................................................................ 39

Figure 3. 4. The scatterplot between apparent clumping index from LAI-2000 and element clumping index estimated from TRAC CC method ........................................................................................................................................ 45

Figure 3. 5. The relation between number of sampling plots and apparent clumping index derived from 20 plots (~120 LAI-2000 readings per plot) in Metolius, Oregon, USA ........................................................................................................................................ 46

Figure 3. 6. The seasonal variation of apparent clumping index with effective leaf area index measured from a temperate deciduous forest (Harvard forest) in 2006 and an invasive weed site (Sherman Island) in 2009 ........................................................................................................................................ 48
Figure 4. 1. Time series of monthly average daily maximum and minimum air temperature, monthly average of volumetric soil water content at 5-cm depth, monthly sum of precipitation, green leaf area index, monthly averaged daily-integrated net radiation, latent heat flux, sensible heat flux, and soil heat flux, and monthly average of bulk surface conductance. 59

Figure 4. 2. Monthly average of daily PAR albedo and the relationships between green leaf area index and PAR albedo during the growing seasons. 61

Figure 4. 3. Monthly average of daily integrated solar radiation and latent heat flux for 6-year. 62

Figure 4. 4. Mean multiyear record of monthly average of daily integrated outgoing and incoming longwave radiation, and monthly average of shortwave broadband albedo. 63

Figure 4. 5. The relationships between monthly average vapor pressure deficit and surface conductance during the 6-year period. 65

Figure 4. 6. Time series of monthly sum of actual evaporation, potential evaporation, and precipitation from July 2001 to June 2007. 67

Figure 4. 7. The relationships between monthly average daily solar radiation and monthly average daily latent heat flux during the 6-year period. The relationship among monthly average daily solar radiation, monthly average volumetric soil water content at 5-cm depth and monthly average daily latent heat flux in May and June during the 6-year period. 68

Figure 4. 8. The relationships between monthly average bulk surface conductance and Priestly-Taylor $\alpha$ coefficient. 70

Figure 4. 9. The relationships between growing season lengths and annual evaporation during the 6-year period. 71

Figure 4. 10. The relationships between annual water deficit and annual actual evaporation. 73

Figure 5. 1. Spectral response of red and near infrared LEDs. 77

Figure 5. 2. Calibration of LEDs derived NDVI sensor for red and NIR bands against a hand-held spectrometer measurements. 79

Figure 5. 3. Diurnal variation of red, NIR reflectance and NDVI. 81

Figure 5. 4. Seasonal to inter-annual variation of rainfall, red and NIR reflectance and NDVI. 83

Figure 5. 5. Time series of daily canopy photosynthesis from eddy flux tower and midday LEDs derived NDVI in 2007. Scatter plot between 8-day mean of midday LEDs derived NDVI and 8-day mean canopy photosynthesis from 2006 January to 2009 July. 86

Figure 5. 6. Contour maps of correlation coefficient between normalized difference spectral indices using two wavelengths (x and y axis) and canopy photosynthesis, leaf area index and nitrogen. 87
Figure 6. 1. Monthly mean diurnal variation of hourly evaporation and the ratio of hourly sum to daily sum for seven sites................................................................. 94

Figure 6. 2. Scatterplot of the ratio of $\lambda E$ sum under clear sky (clearness index >0.6) to $\lambda E$ sum for all sky conditions versus the yearly average clearness index from 1000 to 1400hh. Scatterplot of the ratio of cloudy $\lambda E$ to clear $\lambda E$ versus the ratio of cloudy $R_g$ to clear $R_g$ conditions... 96

Figure 6. 3. Contour plot of the ratio of monthly mean $S_e$ from 1000-1400hh to monthly mean 24-hour $S_e$ against months and northern latitudes. Yearly averaged ratio of monthly mean 24-h $S_e$ for 24h to monthly mean $S_e$ from 1000-1400hh................................................. 98

Figure A2. 1. The probabilities of the number of trees counted in the subsample areas corresponding to the projection of mean tree crown on the horizontal surface at the view zenith angles of 8, 22, 37, 52, 67, and 82................................................................. 125

Figure A2. 2. The ratio of gaps between crowns to total gaps among four tree species simulated by Nilson (1999) model................................................................. 126

Figure A5. 1. Schematic of LED NDVI sensor with a list of parts ......................... 127

Figure A5. 2. LED-spectrometer head ................................................................. 128

Figure A5. 3. Relative response of the red and NIR LEDs compared with the ideal cosine curve................................................................. 129

Figure A6. 1. Scatterplot of 8-day, 24-h $\lambda E$ means against mid-day single-hourly means of $\lambda E$ for the corresponding 8-day periods for each PFT and hour around noon................. 130
**List of Tables**

Table 2. 1. Description of measurements, processing, and characteristics of indirect instruments to estimate leaf area index………………………………………………………………………………… 9

Table 2. 2. Leaf inclination angle measured at six height levels …………………………… 15

Table 2. 3. Element clumping index calculated from eight methods …………………… 18

Table 3. 1. LAI-2000 raw data survey from 39 sites……………………………………… 40

Table 4. 1. Annual energy balance closure for linear regression coefficients and the ratio of $\lambda E + H + G$ to $R_n$. …………………………………………………………………………… 54

Table 4. 2. Summary of energy fluxes, climatology, and bulk parameters for the 6-year ……………………………………………………………………………………………… 57

Table 5. 1. Leaf-on and leaf-off dates recorded from field observation (weekly to bi-weekly) and LEDs system……………………………………………………………………………… 84

Table 6. 1. Site information……………………………………………………………… 91

Table 6. 2. Statistics for linear regression of 8-day average $\lambda E$ versus hourly-average $\lambda E$ for data grouped by hour and plant function types………………………………………………… 95

Table A6. 1. Site information  …………………………………………………………… 131
Acknowledgements

I thank the UC Berkeley that allowed me to freely explore new opportunities in science and life. That leads me to thank again to Drs. Dowon Lee, Joon Kim, Sinkyu Kang and Josh Fisher who wrote recommendation letters for me when applying the ESPM, UCB. The UCB professors-Todd Dawson, John Chiang, Peng Gong, and Jim Kirchner among many others- taught me how to think.

I got three lessons from my adviser, Dennis Baldocchi: 1) be creative, 2) be positive, and 3) be generous. Almost everyday morning he stopped by my office and we talked about everything, including science. In my 1st year, it was really helpful to improve my English, but it turned out that our daily discussion made fertile soil for my PhD course, and life. When he offered me the PhD course position, he wrote that “My goal and responsibility is to try and attach research funds to support you in addition, and/or help students like you apply for NASA, DOE Global Change Fellowships.” He was really supportive in the additional funding, and of course, fellowship proposal, which led to the NASA Earth System Science Fellowship. He always paid attention to my questions although they are often stupid; he encouraged me to develop next questions; and I learned how question-oriented work can advance the science. He exemplified how to be a good scientist, father and husband- he was really well balanced person that I am now striving for. When my father unexpectedly passed away, he paid the plane ticket to Korea for me using his personal money- it was only a small piece among numerous examples in his kindness and warm heart that I have seen. Yes, in a nutshell, thanks Dennis.

Biomet people showed me how collaborative manner, rather than competitive, can produce exciting works. Siyan was always there when I have any question on our field data; Oliver got complaints from Julie for our all day discussion, including night; Rodrigo, this guy is fantastic, no any other word is not necessary; Hideki made my PhD work fruitful and most strong impression on him is that he only had two dishes in 25$ buffet!; Matteo was a tutor on MATLAB and micrometeorology; Jaclyn always reviewed my manuscripts with big smiles; Jessica and Naama shared tough experience for babies with me; Joe enabled my ideas to be realized in the field.

My study on the canopy architecture would be not possible without two giants’ assistance and encouragement: Drs. Tiit Nilson and John Norman. I was wondering the definition on the spherical leaf inclination angle and sent emails to them with little expection of their response because I presumed they were already retired. However, their responses were much faster than any other person I have corresponded. John always encouraged me to closely look at the canopy architecture and his responses were 10X longer than my question. Tiit taught me on the gap fraction and clumping effects. His response was very clear based on physics and mathematics. I met John in Apr 2010, and look forward to meeting Tiit in the near future.

Microsoft supported my tuition fee and summer salary through the PhD course. It provided a fantastic opportunity to collaborate with computer scientists. Even though not included in the thesis, developing global map of GPP and evaporation was a main project in the PhD course, which will be finished this summer. The collaboration with Microsoft enabled me to explore unprecedented opportunities to look at spatial and temporal patterns of land fluxes at the global
scale over the 10-year via the cloud computing system. Jie, Catharine, Deb, and Keith exemplified how collaboration between different fields can produce a cutting-edge science. In particular, I really appreciate Jie from U Virginia. He was so supportive, nice, kind, diligent and generous. I know he will make an excellent thesis.

My thanks extend to the UCB Day care center. The subsidy program provided excellent day care system with amazingly low fee. In particular, Cynthia and Tram took care of my first baby last two years. Their warmth won’t be forgotten.

I would like to thank my family. My lovely wife, Eunjin, has done unbelievable works within the four years. She delivered two babies, Jaein and Jaehwee; she finished her master course at San Francisco Conservatory of Music; she served as a conductor and singer in church; she made uncountable yummy foods; she greatly cared the babies. Without Eunjin’s dedicated support, I could not finish my thesis in the four year. Jaein and Jaehwee offered a full of joy in my life. I hope they grow up with creative, positive and generous mind. I thank my mom for her endless support. She taught me to respect for nature. My father-in-law and mother-in-law showed me the importance of positive mind.

Finally, I thank to my late dad. We enjoyed many sports including tennis, baseball, ping-pong, swimming and basketball. His love was unconditional, his life was enthusiastic. I love you, I respect you, and I miss you. I will deliver your spirit to your grand children.

This dissertation was supported by NASA Headquarters under the NASA Earth and Space Science Fellowship Program (NNX08AU25H), the Berkeley Water Center/Microsoft eScience project, and the Office of Science (BER), the U.S. Department of Energy (DE-FG02-03ER63638). International House provided financial aid in 2010 spring.

Portions of this dissertation have been reprinted, with permission, from previously published materials. Chapters 2 and 3 have been reprinted from Agricultural and Forest Meteorology, Elsevier. Chapter 4 has been reprinted from Journal of Geophysical Research-Atmospheres, American Geophysical Union. I thank their permission.
Chapter 1: Introduction

*It is the pervading law of all things organic and inorganic,*
*Of all things physical and metaphysical,*
*Of all things human and all things super-human,*
*Of all true manifestations of the head,*
*Of the heart, of the soul,*
*That the life is recognizable in its expression,*
*That form ever follows function. This is the law.*

(Sullivan 1896)

Savannas exist in water-limited regions, which force tree canopies open and heterogeneous (Eagleson and Segarra 1985; Rodriguez-Iturbe et al. 1999; Sankaran et al. 2005). The open canopy structure allows grass to co-dominate in the savannas by occupying different niches in space and time. The co-dominance of trees and grass defines the functions and metabolisms in the savanna ecosystems (Higgins et al. 2000; House et al. 2003; Scholes and Archer 1997). However, how to quantify canopy architecture and how to monitor structure, function, and metabolism in savanna ecosystems remains challenging.

The main variables in canopy architecture include leaf area index, leaf inclination angle, and foliar clumping index, which all controls light interception by leaves thus canopy photosynthesis (Ross 1981). In particular, the leaf area index is a central variable to modulate water, carbon, energy and momentum exchanges between land and atmosphere (Baldocchi and Meyers 1998; Norman 1982; Norman and Jarvis 1974). However, quantification of leaf area index in an open canopy presents a challenge because most indirect methods were developed for the ideal and closed canopies (Welles and Norman 1991).

Chapter 2 reports on the quantification of leaf area index and associated canopy structure variables like leaf inclination angle and foliar clumping index using a multi-model and multi-instrument approach in an open savanna ecosystem (Ryu et al. 2010).

Two questions raised from Chapter 2 include how much natural vegetation is different from an ideal, closed canopy and how the difference influences the estimation of LAI indirectly. The indirect methods to estimate leaf area index relies on the beam penetration through the canopy by assuming turbid media of canopy. Thus it has been known that the indirect methods provide effective leaf area index that does not include foliar clumping effects (i.e. actual leaf area index=effective leaf area index/clumping index) (Black et al. 1991; Chen 1996). There have been diverse efforts to quantify clumping effects at shoot (Chen et al. 1997; Norman and Jarvis 1975), crown (Chen and Cihlar 1995b; Leblanc et al. 2005; van Gardingen et al. 1999), and ecosystem levels (Ryu et al. 2010). However, there have been few efforts to obtain theoretically consistent effective leaf area index. Chapter 3 reports on the correct estimation of effective leaf area index using across a range of vegetation types. Furthermore, this chapter sheds light on the new avenue to infer foliar clumping effects from the indirect methods and presents how the foliar clumping effects at each plant functional types deviate from the ideal, closed canopy.
Grass in the savannas has shallow roots which limits to access to the deeper water. How grass in the savannas responds to environmental/biological factors is an important issue to understand and predict the functions of grass in a changing climate. Chapter 4 reports on the interannual variability of evapotranspiration and energy exchanges in an annual grassland (Ryu et al. 2008a). This chapter focuses on 1) how water and energy controls evapotranspiration in energy-limited and water-limited periods within a hydrological year, 2) how length of growing season modulates annual evapotranspiration rate, 3) how rainfall in May affects the peak leaf area index and consequently, evapotranspiration rate.

To bridge ecosystem structure, function and metabolism, continuous monitoring system on the vegetation status is urgently needed. Manual observation should be more accurate but it is not continuous. Satellite remote sensing could be useful for this purpose but its signal is often contaminated by atmospheric conditions (e.g. aerosol, cloud). Thus developing and testing a near-surface remote sensing system is warranted. Chapter 5 reports on a novel spectral reflectance sensor equipped with light emitting diodes. I focus on the performance of this inexpensive, simple but reliable sensor to infer ecosystem structure, function and metabolism in an annual grassland using the 3.5 years data. Also I show the flexibility of this system by selecting the best combination of two wavebands.

Satellite remote sensing data is appealing to upscale eddy covariance measurements into the large areas. However, the regular monitoring of land surface fluxes from satellites has been limited because of discontinuous temporal coverage. Chapter 6 reports on a temporal upscaling scheme from instantaneous evapotranspiration derived from satellites to 8-day mean daily-sum evapotranspiration. I use the 26 flux tower data that covers six plant functional types from boreal to tropical climate zones.
Chapter 2: How to quantify tree leaf area index in an open savanna ecosystem

2. 1. Introduction

Savannas exist in water-limited regions where potential evaporation exceeds precipitation (Baldocchi and Xu 2007; Joffre et al. 2007; Ryu et al. 2008a). As a result, savannas have evolved with heterogeneous, open canopies (Eagleson and Segarra 1985; Rodriguez-Iturbe et al. 1999; Sankaran et al. 2004). This canopy openness presents a challenge for evaluating tree leaf area index (L, nomenclature is summarized in Appendix 2. 1), as most methods were developed for ideal and closed canopies (e.g. Welles and Norman, 1991). To date, only a few studies have used indirect methods in savannas (Hoffmann et al. 2005; Privette et al. 2004; Scholes et al. 2004), yet critical questions remain unanswered: What are the strengths and weaknesses among the methods? How can we reliably measure L indirectly in a savanna?

The questions asked in the study are critical because L, one-sided leaf area per unit ground area (Watson 1937), is a key variable to link structure and function of ecosystems. First, the intercepted radiation is mainly determined by L, and is related directly to the amount of CO₂ assimilation through photosynthesis (dePury and Farquhar 1997; Norman 1982). Second, L has implications for hydrological ecosystem dynamics because L controls rainfall interception (Aston 1979), canopy evapotranspiration (Baldocchi et al. 2002; Leuning et al. 1995), and soil evaporation (Kelliher et al. 1995; Schulze et al. 1994). Third, L determines the area involved in emissions and depositions of trace gases such as isoprene, NOx and SOx (Baldocchi et al. 1999; Hicks et al. 1987).

Direct and indirect methods are used to quantify L, but there are several challenges and limitations for their application in savannas. Direct methods include the collection of leaves through either destructive sampling (Gower and Norman 1991), litterfall traps (Marshall and Waring 1986), allometric relations (Gower and Norman 1991), or using the stratified-clip method (Hutchison et al. 1986; Monsi and Saeki 1953). Indirect methods use mathematical and radiative transfer theory to estimate L from more easily and faster measurable variables such as contact number (K) and gap fraction (Pₒ). For the inclined point quadrat method, a thin probe inserted at a certain angle into short canopies counts the number of contacts between probe and leaves to calculate L (Warren Wilson 1959, 1960). The measurement of Pₒ allows estimation of L regardless of canopy height. Most commercially available instruments for the indirect optical measurement of L such as the LAI-2000 plant canopy analyzer (LI-COR, Lincoln, NE, USA) or hemispherical photography (Bonhomme and Chartier 1972; Neumann and Den Hartog 1989; Zhang et al. 2005) are based on the Pₒ theory (e.g. Nilson 1971). It should be noted that Pₒ theory-based indirect methods assume closed and homogeneous canopies.

---

1 This chapter is reprinted, with permission, from the original journal article: Ryu, Y., Sonnentag, O., Nilson, T., Vargas, R., Kobayashi, H., Wenk, R., & Baldocchi, D.D. (2010). How to quantify tree leaf area index in a heterogeneous savanna ecosystem: A multi-instrument and multi-model approach. Agricultural and Forest Meteorology, 150, 63-76
To obtain spatially representative $P_o$ estimates using indirect methods, we have to address questions related to sampling design, instrument performance, and $P_o$ averaging method at the ecosystem scale. Sampling design for $P_o$ measurements is crucial in heterogeneous, open canopies but has not been fully explored. Because of savannas’ canopy openness and heterogeneity and instrument accuracy, determination of the adequate method to measure $P_o$ is elusive but critical. Thus, it is essential to evaluate and constrain indirect measurements of $P_o$ with independent $P_o$ models. Another important issue is the averaging of $P_o$ (i.e. $\ln(P_o)$) (Fassnacht et al. 1994; Lang and Xiang 1986), which may result in different estimates of $L$. We could expect that two $P_o$ averaging methods may result in similar $L$ estimates for homogeneous, closed canopies. In contrast, increasing spatial variability of $P_o$ may result in substantially different $L$ estimates. We postulate that in heterogeneous savanna ecosystems the difference between the two $P_o$ average methods would be very different as reported by Lang and Xiang (1986).

Another critical variable used for indirect methods in heterogeneous savannas is the clumping index ($\Omega$). This index quantifies the spatial distribution pattern of leaves (Nilson 1971; Norman and Jarvis 1974). It has been usually quantified based on gap size distribution measured from Tracing Radiation and Architecture of Canopies instrument (TRAC; 3rd Wave Engineering, ON, Canada) or digital hemispherical photography (DHP) (Chen and Cihlar 1995a; Leblanc 2002; Leblanc et al. 2005; Norman and Jarvis 1974; van Gardingen et al. 1999). Main challenges to quantify and interpret $\Omega$ in savannas include the range of view zenith angle ($\theta_V$), the type of calculation methods, and how $\Omega$ changes with $\theta$. Because $\Omega$ changes with $\theta$ (Andrieu and Sinoquet 1993; Chen 1996; Kucharik et al. 1999; Norman and Welles 1983), several $\Omega$ values covering a wide range of $\theta$ are required to calculate hemispherical average $\Omega$ value. The length and number of transects and sampling time must be compromised to obtain spatially representative $\Omega(\theta)$ that covers zero to $\pi/2$ of $\theta$ adequately because the TRAC instrument has to be walked at slow pace (~0.3 m s$^{-1}$) (Leblanc et al. 2002). Most studies using the TRAC instrument are based on a limited number of $\Omega(\theta)$ estimates within narrow and moderate range of $\theta$ including 30-80° (Chen 1996), 25-50° (Law et al. 2001b), 30-50° (Hall et al. 2003) and 57.5° (Jonckheere et al. 2005). However, few studies have examined whether those narrow range estimates of $\Omega(\theta)$ are sufficient to be spatially representative. Various approaches have been proposed to calculate $\Omega$, namely Lang and Xiang (1986) (hereinafter LX), Chen and Cihlar (1995) (hereinafter CC), and the combination of LX and CC (Leblanc et al. 2005) (hereinafter CLX). Importantly, there was considerable difference among different methods to calculate $\Omega$. For example, based on 29 boreal forest site measurements, Leblanc et al (2005) reported the mean $\Omega$ values calculated from CC, LX and CLX are 0.9, 0.79 and 0.67, respectively. Finally, angular dependence of $\Omega$ is an important characteristic to determine spatially representative $\Omega$ value. Previous studies from boreal and temperate forests reported that $\Omega$ increased with $\theta$ (Chen 1996; Kucharik et al. 1999; Leblanc et al. 2005), yet it is unclear whether this relation is valid in savanna canopies.

Another key variable for the indirect quantification of $L$ is the leaf inclination angle ($\theta_L$), commonly defined as the angle between the leaf surface normal and the zenith (Ross 1981). The leaf inclination angle distribution function $f(\theta_L)$ describes the leaf inclination angle distribution as the probability density function (de Wit 1965; Idso and de Wit 1970). The $f(\theta_L)$ plays a
fundamental role in the leaf projection function (commonly referred to as $G$-function), which
describes the projection of unit foliage area on the plane perpendicular to the view direction
(Myneni et al. 1989; Ross 1981). The $G$-function is essential to calculate $P_o$ at specific view
zenith angles. In spite of its importance, most studies assume spherical $f(\theta_L)$ because of the
difficulty in estimating $\theta_L$. Various instruments for the in-situ the measurement of $\theta_L$ have been
proposed (Kucharik et al. 1998a; Lang 1973; Smith and Berry 1979; Smith et al. 1977), but their
wide-spread use has been generally hampered due to difficulties in applying them to tall canopies,
and due to their unsatisfactory ability to reproduce measurements. Several sophisticated
approaches including a 3-dimensional digitizer (Falster and Westoby 2003; Sinoquet et al. 2009)
and a ground based light detection and ranging (LiDAR) (Hosoi and Omasa 2007) have
quantified 3-dimensional leaf arrangement but high economic costs prevent their routine
application. Thus, development of a robust, affordable method that allows for reproducible
measurements of $\theta_L$ regardless of canopy height is warranted. Here we introduce a digital
photography based method that meets these criteria.

The goal of this study is to determine spatially representative tree $L$ at ecosystem scale in an oak-
savanna canopy in California, USA. To achieve this goal, we measured $\theta_L$, characterized $P_o$ and
$\Omega$ based on multiple indirect methods and models, and finally quantified $L$, which we evaluated
with directly-measured $L$. The scientific questions we address include: (1) What are the strengths
and weaknesses of multiple methods to assess $L$ in heterogeneous, open canopies? (2) How to
estimate spatially representative $\Omega$ in a savanna? We hypothesize that: (1) $\Omega$ may increase with $\theta$
in a heterogeneous savanna as reported in previous studies (Chen 1996; Kucharik et al. 1999).
This is expected because longer path lengths with increasing $\theta$ would decompose large gaps into
smaller ones (i.e. less clumped); and (2) the influence of gaps between crowns on total $P_o$ may be
dominant in the savanna site because of the open canopy. Finally, we suggest a protocol to
quantify $L$ and its associated canopy structure variables in open canopy ecosystems.

2. 2. Theoretical background

2. 2. 1. Leaf projection function and leaf inclination distribution function

The leaf projection function ($G$) is the projection coefficient of unit foliage area on a plane
perpendicular to the view direction (Ross 1981). The quantification of $G$ requires knowledge of
$f(\theta_L)$. Several approaches have been developed to characterize $f(\theta_L)$ including a non-parametric
function (de Wit 1965), an one-parameter ellipsoidal distribution function (Campbell 1990), and
a two-parameter Beta-distribution function (Goel and Strebel 1984). The two-parameter Beta-
distribution function has recently been identified as being the most accurate for describing the
probability density of $\theta_L$ (Wang et al. 2007):

$$f(t) = \frac{1}{B(\mu, \nu)}(1-t)^{\mu-1}t^{\nu-1}$$

where $\mu$ and $\nu$ are two parameters, $t$ is $2\theta_L/\pi$, $\theta_L$ is leaf inclination angle, and $B(\mu, \nu)$ is the Beta-
distribution (Pitman 2006):
\[
B(\mu, v) = \int_0^1 (1-x)^{\mu-1} x^{v-1} dx = \frac{\Gamma(\mu)\Gamma(v)}{\Gamma(\mu + v)} \tag{2.2}
\]

where \(\Gamma\) is Gamma function. Assuming a uniform distribution of leaf azimuth orientation, \(G\) may be expressed as (Warren Wilson 1960, 1967):

\[
G(\theta) = \int_0^\pi/2 \phi(\theta, \theta_L) f(\theta_L) d\theta_L \tag{2.3}
\]

\[
\phi(\theta, \theta_L) = \begin{cases} 
\cos \theta \cos \theta_L & |\cot \theta \cot \theta_L| > 1, \\
\cos \theta \cos \theta_L [1 + (2/\pi)(\tan \theta + \theta)] & \text{otherwise}
\end{cases} \tag{2.4}
\]

where \(\theta\) is solar zenith angle and \(\theta = \cos^{-1}(\cot \theta \cot \theta_L)\). Values for \(G(\theta)\) range from zero to one and generally converge at \(-0.5\) for all \(f(\theta_L)\) when \(\theta = 1\) radian (\(\approx 57^\circ\)) (Lang et al. 1985; Nilson 1971; Ross 1981; Warren Wilson 1960).

### 2.2.2. Gap fraction and leaf area index

Monsi and Sacki (1953; 2005) first proposed \(P_o\) theory. Under certain conditions the probability of beam penetration can be described by the Poisson distribution:

\[
P_o(\theta) = \exp(-G(\theta)L_t / \cos \theta) \tag{2.5}
\]

where \(P_o(\theta)\) is the gap fraction in dependence of solar zenith angle \(\theta\) and \(L_t\) is total plant area index that includes leafy and woody components. The main assumption underlying Eq. (2.5) is that the positions of phytoelements are randomly distributed. By taking the logarithm of Eq. (2.5), the contact number \(K\) can be derived:

\[
K(\theta) = -[\ln P_o(\theta) / \cos \theta] = G(\theta)L_t \tag{2.6}
\]

The inverse estimation of \(L_t\) from \(P_o\) measurements (Eq. 2.6) requires knowledge of \(G\), which is usually unknown. To overcome this limitation, Miller (1967) proposed a theorem for the inverse estimation of \(L_t\) that does not require a prior knowledge of the \(G(\theta)\):

\[
L_t = 2 \int_0^{\pi/2} K(\theta) \sin \theta d\theta = 2 \int_0^{\pi/2} -[\ln P_o(\theta) / \cos \theta] \sin \theta d\theta \tag{2.7}
\]

The Eq. 2.7 forms the underlying principle of the LAI-2000 instrument by using diffuse radiation to avoid the strong dependency of the direct solar beam to latitude and seasonality (Welles and Norman 1991). Another approach to avoid \textit{a-priori} knowledge of the \(G(\theta)\) is to measure \(P_o(\theta)\) at \(\theta = 1\) radian. If the direct beam radiation is used to estimate \(L_t\) other than 1 radian \(\theta\), then one must quantify \(G(\theta)\) as shown in Eq. 2.3.

To consider the non-random spatial distribution of leaves, Nilson (1971) first proposed a Markov-chain model introducing an additional quantity, \(\Omega\), into Eq. 2.5:

\[
P(\theta) = \exp(-G(\theta)L_t \Omega(\theta) / \cos \theta) \tag{2.8}
\]
Clumping index is expressed as follows: (Chen 1996):

$$\Omega = \frac{\Omega_E}{\gamma_E}$$  \hspace{1cm} (2.9)

where $\Omega_E$ is element clumping index that quantifies foliage clumping at scales larger than the shoot and $\gamma_E$ is the needle-to-shoot area ratio for shoot-scale clumping. Usually, $\gamma_E$ is assumed to be 1 for deciduous broad-leaved trees (Chen 1996).

Retrieval of $L_t$ on the basis of measured $P(\theta)$ and inversion of Eq. 2.7 results in effective leaf area index ($L_e$) which includes the contribution of all light-intercepting canopy elements (including green and dead leaves, branches, trunks and attached mosses and lichen) assuming their random distribution in space (Black et al. 1991):

$$L_e = L_t \times \Omega$$  \hspace{1cm} (2.10)

For a random spatial distribution of all light-intercepting canopy elements (i.e. $\Omega = 1$) $L_e = L_t$. A limitation of $P_o$ based approaches is their inability to discriminate between canopies’ woody components including attached mosses, lichens, dead leaves, branch and stems from green foliage. For ecosystem with moderate to high values for $L$, leaves cover most woody components and the probability of a direct beam radiation to hit the woody component is very low (Kucharik et al. 1998b). Thus, the effect of woody components on the $P_o$ estimate may be marginal and ignorable. However, in ecosystems with lower values for $L$ such as savannas, the contribution of woody components to $P_o$ estimate may not be ignorable, and we decided to subtract woody area index ($W$) (Privette et al. 2004) from $L_t$ in Eq. 2.10:

$$L = \frac{L_e - W}{\Omega}$$  \hspace{1cm} (2.11)

Obtaining spatially representative estimates of $L_e$, $\Omega$, $W$ and $L$ is challenging in a heterogeneous ecosystem. In this study, we show the acquisition of each variable based on multiple instruments and models.

2.3 Methods

2.3.1 Site description

The study site is Tonzi Ranch (latitude: 38.431°N; longitude: 120.966°W; altitude: 177 m) located in the lower foothills of the Sierra Nevada Mountains, Ione, CA, USA. The site is part of AmeriFlux (http://public.ornl.gov/ameriflux/) and is classified as an oak-grass savanna woodland. The site is on flat terrain (average slope: 1.5°) and experiences Mediterranean-type climate with dry, hot summers and rainy, mild winters. Annual average temperature and annual precipitation are 16.9°C and 565 mm, respectively (1949 to 2005 climate normals from Camp Pardee climate station; latitude: 38.25°N; longitude: 120.85°W). The overstory consists of dominant blue oak trees ($Quercus douglasii$) with occasional (< 10%) grey pine trees ($Pinus sabiniana$). The understory is mainly composed of grasses and forbs ($Brachypodium distachyon$, $Hypochaeris glabra$, $Bromus madritensis$, $Cynosurus echinatus$) (Baldocchi et al. 2004). Due to the low density of grey pine trees ($Pinus sabiniana$), we assumed $\gamma_E = 1$ and thus $\Omega = \Omega_E$ (Eq. 2.9). The stem density was 144 ha$^{-1}$, tree height was 9.4 ± 4.3 m (mean ± standard deviation), trunk height
was 1.8 ± 1.3 m, diameter at breast height (DBH) was 0.26 ± 0.11 m, mean crown radius was 2.9 ± 1.4 m, and canopy cover was 0.47 (Chen et al. 2008). More detailed site information may be found in previous studies (Baldocchi et al. 2004; Chen et al. 2008; Ma et al. 2007).

2. 3. 2 Sampling design, measurements, and data processing

2. 3. 2. 1 Sampling design
We established a 300×300 m sampling plot with the micrometeorological tower at the center and gridded at 30×30 m intervals (Figure 2. 1a). The extent of the plot corresponds to the scale of spatial heterogeneity as determined through semivariogram analysis (Kim et al. 2006). A grid size of 30-m was chosen to minimize oversampling by different instruments. For example, the field-of-view of the LAI-2000 instrument is approximately three times the canopy height (~27 m). Field data was collected with the LAI-2000, TRAC, DHP, and digital cover photography (DCP) from Aug 5 to Aug 7, 2008, i.e. near the peak of the growing season (Table 1). Technical problems with an automatic traversing radiometer system (TRS) required us to use data from three days (25, 27, and 29 July 2008) close to the intensive field measurement dates. To estimate woody area index (W), we made 33 additional measurements of LAI-2000 along three transects during the leafless period on 31 Jan 2009, and 58 additional measurements of DCP at the same three transects (n=33) and at the litterfall trap locations (n=25) (see 3.2.8) on Mar 16, 2009. In 2006, we installed a 150 x 150 m subplot directly upwind of the flux sensor (Fig 1a) to develop an independent estimate of the woodland carbon budget from direct measures of primary production. As part of this effort, we inventoried all the trees and installed 25 litterfall traps (opening area = 0.16 m²; height = 1.5 m) at regular intervals (25 m apart) in the interior of the plot. Table 1 summarizes the description of instruments. In the following sections, we first explain the leaf inclination angle measurement, then indirect instruments to estimate L, and lastly direct methods to estimate L employed in this study.

Figure 2. 1. (a) Plot design laid over IKONOS image taken on Sep 2001. The eddy covariance flux tower is located at the center (white triangle). The plot extent was 300 x 300 m, which was subdivided with a 30x30 m grid. LAI-2000 was measured at all intersected points of gridded yellow line of the subplots (i.e. 121 points). DHP and DCP were measured at red circles. TRAC
was measured over four sub-transects (blue lines). Litterfall collectors were installed in a 25 x 25 m grid within a 150 x 150 m plot (dashed white line) within the footprint of the tower and the large 300 x 300 m plot. Tram was located north of the flux tower (white line). (b) A schematic diagram of protocol used to measure leaf inclination angle (not drawn to scale).

Table 2. 1. Description of measurements, processing, and characteristics of indirect instruments to estimate $L$ employed in this study. aRanges about TRAC, DCP and RTC were obtained from several measurements at different solar zenith angles. bChen and Cihlar 1995. cCombination of LX and CLX (Leblanc et al 2005). dEffective leaf area index

<table>
<thead>
<tr>
<th></th>
<th>LAI-2000</th>
<th>Tracing radiation and canopy architecture (TRAC)</th>
<th>Digital hemispheric photography (DHP)</th>
<th>Digital cover photography (DCP)</th>
<th>Traversing radiometer system (TRS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spatial sampling number (sampling number in leafless dates)</td>
<td>121 (30)</td>
<td>4</td>
<td>47</td>
<td>47 (58)</td>
<td>1</td>
</tr>
<tr>
<td>Transect length, (raw data acquisition frequency)</td>
<td>-</td>
<td>90-m (32 Hz)</td>
<td>-</td>
<td>-</td>
<td>30-m (10 Hz)</td>
</tr>
<tr>
<td>Number of view zenith angles</td>
<td>5 (no exclusion of outer rings)</td>
<td>1</td>
<td>various</td>
<td>1 (zenith)</td>
<td>1</td>
</tr>
<tr>
<td>Range of view zenith angles $^a$</td>
<td>7-68</td>
<td>25-77</td>
<td>10-80</td>
<td>0-13</td>
<td>19-80</td>
</tr>
<tr>
<td>Calculation method of clumping index in this study</td>
<td>-</td>
<td>CC$^b$, CLX$^c$</td>
<td>CC, CLX</td>
<td>CC</td>
<td>CC, CLX</td>
</tr>
<tr>
<td>Necessity of leaf inclination angle information to get $L^s$</td>
<td>X</td>
<td>O</td>
<td>X</td>
<td>O</td>
<td>O</td>
</tr>
<tr>
<td>Illumination condition</td>
<td>Diffuse</td>
<td>Direct</td>
<td>Diffuse</td>
<td>Direct/diffuse</td>
<td>Direct</td>
</tr>
</tbody>
</table>

2. 3. 2. 2 Leaf inclination angle

We used a high definition digital camera (LUMIX, Panasonic DMC-F250, Secaucus, NJ, USA) using a fixed zoom lens (10x) and leveled by a 1.3 m tripod to measure $\theta_L$. We took digital photographs of the surrounding oak canopy (north, east, west, south) using the tower (Figure 2.1b). Photographs in all four directions were taken at six height levels at 2 m increments. An average of around 50 images per level resulted in a total of 304 images. Total 11 trees contributed $\theta_L$ measurements. Because of the big holes within crowns, we also took the inner crown leaves. To comply with the definition of $\theta_L$, we only selected leaves oriented approximately parallel to the viewing direction of the camera (Figure 2.1b). We only selected leaves seen as line to exclude bent leaves. We manually estimated $\theta_L$ using the angle measurement tool of a public domain image processing software (ImageJ; http://rsbweb.nih.gov/ij/). At each height level, we measured $\theta_L$ for 200 leaves resulting in a total of 1200 leaves for all levels.
2.3.2.3 LAI-2000
The LAI-2000 instrument measures $P_d(\theta)$ at five concentric rings (ring 1: 0-13°; ring 2: 16-28°; ring 3: 32-43°; ring 4: 47-58°; ring 5: 61-74°) over the hemisphere based on the detection of blue diffuse light (400-490 nm) penetrating the canopy (Welles and Norman 1991). One LAI-2000 unit continuously recorded (15 sec interval) blue diffuse light at the top of the tower as reference. Using a second LAI-2000 unit, an operator took one measurement at each measurement location when sun is lower than the top of canopy to make sure diffuse sky condition. A 180° view cap was used on each sensor to avoid the appearance of the operator on the sensor and block potentially remaining direct light. The operator always stood between the sensor and the declining sun. Throughout this paper, we used $L_e$ derived from $\ln(P_a(\theta))$ approach to avoid over-correction of clumping effect (Ryu et al. 2009a).

2.3.2.4 Tracing radiation of canopy and architecture
The TRAC instrument allows for the indirect measurement of $\Omega_E$, $L_e$, and $L_t$ in the field based on a gap size distribution theory (Chen and Cihlar 1995a; Leblanc et al. 2005). We used the TRAC instrument along four 90 m EW-oriented segments (Figure 2.1a). To estimate spatially representative $\Omega_E$, we employed TRAC instrument at each transect segment in approximately two-hour intervals over the course of a day and thus at different values for $\theta$, resulting in five raw data sets per transect segment. All TRAC measurements were post-processed using the TRACWin software (v4.1.1) (Leblanc 2008).

From each transect measurement, the accumulated $P_a$ derived from the measured gap-size distribution function determines $P_a(\theta)$ (Chen and Cihlar 1995a; Leblanc 2002). We averaged $P_a(\theta)$ measured from four transects over 10-degree intervals of $\theta$ and we used the $P_a(\theta)$ in Eq. 2.7 to calculate $L_e$. We calculated two sets of $\Omega_E(\theta)$ using CC and CLX methods as provided by TRACWin software, and then calculated $\Omega_E$ for each method as:

$$\Omega_E = \frac{\int_m^M \Omega_E(\theta) \sin(\theta) d\theta}{\int_m^M \sin(\theta) d\theta}$$

(2.12)

where M and m are maximum and minimum $\theta$, respectively.

2.3.2.5 Digital hemispherical photography
With digital hemispherical photography (DHP), estimates of $\Omega_E$, $L_e$, and $L_t$ are obtained by measuring $P_a$ and gap-size distribution (Leblanc 2008). We randomly selected three north-south transects and three east-west transects with a total length 270 m (Figure 2.1a). At each measurement point, we took a hemispherical photograph. All DHPs were taken with a 4 mega pixels Nikon CoolPix4500 digital camera using the finest available resolution, and a FC-E8, Nikon fisheye lens with a field-of-view of 183° was attached to the camera. All photographs were taken near sunset or sunrise. We chose the following settings for the camera: 1) manual mode, 2) fish-eye lens, fixed with centrally weighted exposure for automatic exposure; 3) manual mode aperture for fixed exposure; 4) high image quality (2272 x 1704 pixel matrix) and 5) JPEG format. Photographs were taken from the sky reference exposure and then corrected with two stops more exposure relative to the open sky conditions (Zhang et al. 2005). At the end of each transect, the open sky conditions were recalibrated because we were able to access open areas easily. The reference sky exposure was always determined with the same camera in an
opening with no obstruction above 15° of the solar zenith angle in all directions using an aperture of F5.3 (Zhang et al. 2005). Digital image processing of the hemispherical images was done using the DHP software v4.5.2 (Leblanc 2008; Leblanc et al. 2005). Thresholds to distinguish leaf from sky were selected manually following the protocol of Zhang et al (2005), and all photographs were processed by the same person. We used a gamma, the factor to enhance raw image of 2.2 (Leblanc 2008). We averaged \( P_\theta(\theta) \) measured from 47 pictures over every 5 degree interval of \( \theta_L \) and we used \( P_\theta(\theta) \) as an input to Eq. 2.7 to calculate \( L_e \). We averaged \( \Omega_e \) from 47 pictures using CC and CLX methods provided by TRACWin software in DHP mode.

2.3.2.6 Digital cover photography

With digital cover photography (DCP), estimates of foliage and crown cover fractions, and crown porosity based on zenith view direction digital photographs taken from below the canopy are obtained. Finally, estimates of \( \Omega_e(0) \) and \( L_i \) can be derived (Macfarlane et al. 2007a; Macfarlane et al. 2007b). The camera (Nikon CoolPix4500, 2272×1704 resolution) was set to automatic exposure, aperture-priority mode, minimum aperture and F2 lens (Macfarlane et al. 2007b). The camera was leveled and the lens was pointed towards zenith. This setup provides a view zenith angle (\( \theta_V \)) from 0 to 15°, which is comparable with the 1st ring in LAI-2000 (Macfarlane et al. 2007b). Before sunset or after sunrise when sun is lower than the top of canopy, a total of 47 photos were taken at the same measurements locations together with DHP from Aug 5 to Aug 7, 2008. The key input parameter to estimate \( L_i \) is the \( G(0) \), and we used 0.44 estimated from measured \( \theta_L \) (see 4.1). To estimate \( W \) from photos taken at a leafless date, the inclination angle of woody components is necessary, which were not systematically quantified in this study. Instead, we took photos at horizontal view for each DCP measurement points thus combination of zenith view and horizontal view photos gave some sense on the branch architecture at each point. Based on the photos and two limits of \( G \) at zenith direction (i.e. 0.85 for planophile and 0.45 for erectophile in Figure 2.2b), we visually determined \( G(0) \) of dominant woody components at each DCP measurement point. We averaged foliage cover fraction and canopy cover fraction from all pictures including non-canopy photos, and then estimated spatially representative \( \Omega_e(0) \) that explicitly considers large gaps. The cover images were analyzed using Adobe Photoshop CS4 (Adobe Systems Incorporated, San Jose, CA, USA) following Macfarlane et al. (2007b).

2.3.2.7 Traversing radiometer system

A traversing radiometer system (TRS) measured incoming and outgoing photosynthetically active radiation (PAR), and net radiation under canopies. A 30-m rail track was setup 1-m above the ground at 30 m apart from the tower (Figure 2.1a). About half of the rail track was situated below the canopy while other half was situated in open space. Two PAR sensors (incoming and outgoing PAR measurements, PAR LITE, Kipp & Zonen, The Netherlands) and one net radiation sensor (NR-LITE-L, Kipp & Zonen, The Netherlands) moved along the rail track at 0.04 m s\(^{-1}\). One round trip took about 24 min. All radiation measurements were made at a frequency of 1 Hz. The data was transferred to a common personal computer set-up at the tower via a wireless local area network. The up- and down-facing PAR sensors continuously recorded incoming and outgoing PAR over the daytime at the same transect, so it may be treated as TRAC-like data. We used the incoming PAR data as input to TRACWin software, and then we estimated \( P_\theta(\theta) \), \( \Omega_e \) and \( L_e \) with same procedures of TRAC data processing (3.2.4).
2. 3. 2. 8. Allometry
Diameter at breast height (1.37 m) of all the trees in the subplot (Fig 1a) was measured in 2006. Subsequently, annual growth was monitored on a random subset of 140 trees with dendrometer bands. We used these annual growth estimates to project 2008 diameters for all live trees in the carbon subplot. We then used allometric relationships for blue oak (Karlik and McKay 2002) to predict leaf area as a function of tree diameter. The allometry based $L$ was calculated as the sum of the leaf area per tree divided by the total plot area (22,250 m$^2$).

2. 3. 2. 9. Litterfall
In 2008, litter was collected three times from the traps in the subplot (Fig 1a) with the last collection timed soon after last leaf fall. Litter was separated into leaves, twigs, and seeds and then oven-dried to a constant weight. We used the sum of these sequential collections to get a total leaf biomass per collector. Specific leaf area (SLA) was determined for a subset (n=48) of oak leaves obtained from the tree times collection. We measured the one-sided area of 10 fresh oak leaves per sample (total leaf number is 480) with the LI-3100C Area Meter (LI-COR, Lincoln, NE, USA). These samples were then dried to a constant weight. Based on these measurements, the mean SLA for blue oak leaves was 91.8 cm$^2$/g (standard error = 1.18 cm$^2$/g). LAI per trap was calculated as leaf biomass per trap $\times$ SLA and then the mean of these 25 values was taken as the best measure as litterfall $L$ for the subplot. There were two individuals of the evergreen tree, grey pine, present within our plot. However no pine needles were found in the traps in 2008. Given the rarity of the pines (2 trees) compared to the oaks (316 trees), we ignored them in our estimates of both allometry based $L$ and litterfall $L$.

2. 3. 3. Gap-fraction models
To test $P_o$ and $\Omega_E$ estimates from the indirect instruments, we used a gap fraction model that explicitly considers clustering of foliages into crowns (Nilson 1999; Nilson and Kuusk 2004), and a 3-dimensional radiative transfer model (Kobayashi and Iwabuchi 2008). Nilson (1999) determines $P_o$ as follows:

$$P_o(\theta) = \exp[-c(\theta)NS(\theta)]$$  \hspace{1cm} (2. 13)

where

$$c(\theta) = \frac{-\ln[1-(1-P_1(\theta))(1-GI)]}{1-GI}$$ \hspace{1cm} (2. 14)

and

$$P_1(\theta) = \exp[-G(\theta)(L/\gamma_E + B)/(NS(\theta)\cos\theta)]$$  \hspace{1cm} (2. 15)

where $N$ is the tree density (trees m$^{-2}$), $S(\theta)$ is the area of projection of the average tree crown envelope on the horizontal plane, $P_1(\theta)$ is the mean $P_o$ in a single tree crown at $\theta$, $B$ is the branch area index, and $GI$ is the relative variance of the number of trees in the area $S(\theta)$ (Fisher’s dispersion index, Appendix B) (Fisher 1954). By assuming that Eq. 2. 8 and 2. 13 give same $P_o(\theta)$, $\Omega_E(\theta)$ may be expressed as follows:

$$\Omega_E(\theta) = c(\theta)N S(\theta) \cos\theta / (G(\theta)(L/\gamma_E + B))$$  \hspace{1cm} (2. 16)

By using $P_o(\theta)$ measured from LAI-2000 during the leafless period as input data into Eq. 2. 13, $B$ may be quantified (Nilson and Kuusk 2004). Thus, the combination of $P_o(\theta)$ measured from LAI-2000 on a leafless date with Nilson (1999) model allows to estimate $W$ as follows:

$$W = B + T$$ \hspace{1cm} (2. 17)

$$T = \pi \times R \times h \times N$$ \hspace{1cm} (2. 18)
where $T$ is trunk area index, $R$ is the mean trunk radius (m), and $h$ is the trunk height (m).

Additionally, the model distinguishes between gaps between crowns and within. The required canopy structure input parameters were obtained from an airborne LiDAR measurement that was taken across a 200×200-m domain including the tower at the center in 2003 (Chen et al. 2007a; Chen et al. 2007b). The LiDAR used discrete return and the average posting density was 9.5 points per square meter. Another key input variable is $f(\theta_L)$ measured using a digital camera (see 3.2.2).

The model of Kobayashi and Iwabuchi (2008) explicitly considers individual tree shapes and positions derived from LiDAR measurement. Similar to Nilson (1999), $f(\theta_L)$ is a key input parameter. Because of pre-determined tree positions and shapes, $P_\theta(\theta)$ at specific locations can be calculated without $\Omega_E$ (i.e. Eq. 2. 5). Within the area covered by the LiDAR scene, we selected a total of 100 points every 20 m. At each point, we calculated $P_\theta(\theta)$ from 5 to 80 degrees of $\theta$ with a 5 degree interval, and then we determined spatially representative $P_\theta(\theta)$ by averaging all points’ $P_\theta(\theta)$ values. By inverting Eq. 2. 8 with input of $P_\theta(\theta)$, spatially representative $\Omega_E(\theta)$ may be quantified. Both models require $L_r$ as an input parameter. We used 1.14 of $L_r$ as a sum of 0.82 of litterfall $L$ and 0.32 of $W$ that was derived from DCP measurements (See Section 4.4.).

2.3.4 Uncertainty and statistical analyses

To investigate the uncertainty associated with sampling design, we used the gridded LAI-2000 measurements within the 300×300 m area (Figure 2.1a). To study the impact of sample size, we selected sample sizes from 1 to 121. For each sample size, we created 10,000 data sets by drawing random subsets of the respective size from all 121 measurements without replacement. Next, we separately calculated the coefficient of variation (standard deviation/average, CV) for the gap fraction of each ring of the LAI-2000 instrument. To study the impact of plot extent, we used plot sizes from 30 m to 270 m over 30 m intervals. For each plot size, we randomly resampled 10,000 plots without replacement within 300×300 m area, and then generated the CV for $L_e$. To quantify error propagation in the calculation of $L_e$, $\Omega_E$, $W$, and $L$, we used the method of moments (Taylor, 1997):

$$s_y = \sqrt{\sum_{j=1}^{n} \left( \frac{\partial y}{\partial x_j} s_{x_j} \right)^2 + 2 \sum_{j=1}^{n} \sum_{k=j+1}^{n} r_{x_jx_k} \left( \frac{\partial y}{\partial x_j} s_{x_j} \right) \left( \frac{\partial y}{\partial x_k} s_{x_k} \right)}$$

(2.19)

where $s$ is the 95% confidence interval (CI), $y$ is the dependent variable, $x$ is the independent variable, $n$ is the number of independent variable, and $r_{x_jx_k}$ is the correlation coefficient between $x_j$ and $x_k$.

We used a Monte Carlo approach to calculate CI for the $L$ estimates based on allometry and litterfall. For each analysis, we generated 1000 realizations of the estimated value by randomly sampling from normal distributions of the individual variables in the component equation (Harmon et al. 2007). The 95% CI for allometry $L$ included the uncertainty in the 2008 diameter projections and the allometric regression error. For litterfall $L$, error propagation included the uncertainty in the SLA determination and the spatial variance among the 25 traps.
We present all data as the mean ± 95% CI. If the 95% CIs of the calculated means did not overlap with each other, then they were considered to be significantly different at $\alpha = 0.05$. All statistical analyses were performed using JMP (SAS Institute Inc. v7.0, 2007, Cary, NC, USA) or Splus (TIBCO Spotfire S+ 8.1, Palo Alto, California).

2. 4. Results

2. 4. 1. Leaf inclination angle distribution function and leaf projection function

Our measurements of $\theta_L$ showed an overall erectophile leaf inclination angle distribution function (Figure 2. 2a). The mean angle was 63° and it did not vary much with height (Table 2). Based on the measurements, a Beta-distribution function was fitted and the $f(\theta_L)$ was developed (section 2.1). Finally, we characterized $G(\theta)$ using $f(\theta_L)$ (Eq. 2. 3). The $G(\theta)$ was close to that of the spherical orientation (black-filled circle in Figure 2. 2b).
Figure 2. 2. (a) Histogram of leaf inclination angle. This includes all samples measured from six canopy levels that span from 1 m to 11 m. (b) Leaf projection function \( G(\theta) \) against view zenith angle \( (\theta_v) \). Erectophile was drawn based on the developed leaf inclination angle distribution function in this study. Planophile, plagiophile, spherical, and uniform cases were drawn for comparison based on de Wit (1965).

Table 2. 2. Leaf inclination angle measured at six height levels (mean ± 95% confidence interval).
<table>
<thead>
<tr>
<th>Leaf inclination angle</th>
<th>2-m</th>
<th>4-m</th>
<th>6-m</th>
<th>8-m</th>
<th>10-m</th>
<th>12-m</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>57±3.3</td>
<td>58±3.1</td>
<td>62±3.1</td>
<td>61±3.1</td>
<td>66±2.9</td>
<td>65±3.0</td>
<td>57±1.3</td>
</tr>
</tbody>
</table>

2.4.2. Gap fraction

Multi-angle $P_o$ values were measured using LAI-2000, TRAC, and DHP and modeled with Nilson (1999) and Kobayashi and Iwabuchi (2008) (Figure 2. 3a). To improve readability, we did not draw the 95% CI but we interpret the results based on these calculations. The DCP only provided $P_o(0)$, which was not significantly different from LAI-2000 and two gap-fraction models within zero to 13° $\theta_v$. Overall, the estimates of $P_o(\theta_v)$ from LAI-2000, Nilson (1999) and Kobayashi and Iwabuchi (2008) were not significantly different. DHP showed significantly higher $P_o$ values among methods between 40 to 70° $\theta$. TRAC showed significantly lower $P_o$ estimates than LAI-2000, DHP, and Kobayashi and Iwabuchi (2008) between 35 to 65° $\theta$. The $P_o$ estimated from gap size distribution function (Chen and Cihlar 1995a; Leblanc 2002) agreed well with the ratio of $P_o$ measured below the canopy to $P_o$ measured at the top of tower (linear regression: $y=0.99x$, $r^2=0.84$, $p<0.001$) (Figure 2. 3b).
Figure 2. (a) Gap fraction ($P_o$) comparison among LAI-2000, DHP, TRAC and DCP sensors with two $P_o$ models using Nilson 1999 and Kobayashi and Iwabuchi 2008. To improve readability, 95% CI was not drawn. (b) Comparison between $P_o$ from direct measurement (the ratio of incoming photosynthetically active radiation (PAR) below canopies measured from a traversing radiometer system (TRS) to incoming PAR above canopies measured from top of flux tower) and $P_o$ calculated from accumulated $P_o$ function (Chen and Cihlar 1995) using the TRS incoming PAR data (sub-box in Figure 2. 3a) on July 25, 2008. The linear regression between two variables gave $y=0.99x$ ($y$: measured, $x$: calculated, linear regression was forced to pass the origin) with $r^2=0.83$. 
2.4.3. Element clumping index
We quantified $\Omega_E$ using several instruments, models and a theoretical equation (Table 3) and we found considerable difference among them. The $\Omega_E$ values were significantly different depending on calculation methods (CLX and CC) for DHP. From Eq. 2.10, $\Omega_E$ can be directly calculated if independent measurements of $L_t$ and $L_e$ exist. $L_t$ from the sum of litterfall $L$ (0.82) and $W$ (0.32, see section 4.4) was 1.14. Spatially representative $L_e$ at ecosystem scale measured from LAI-2000 was 0.56 (section 4.5). Thus, $\Omega_E$ estimated from $L_e/L_t$ was 0.49±0.02, which was significantly different from all other methods that reported 95% CI. We determined 0.49±0.02 to be the spatially representative $\Omega_E$. The indirect methods based $L_e/L_t$ can be quantified by combining DCP (for $L_t$) and LAI-2000 (for $L_e$) (DCP-LAI2000 in Table 2), and its estimate was 0.49±0.10.

Table 2.3. Element clumping index ($\Omega_E$) calculated from eight methods. Estimates were reported with mean± 95% confidence interval. aDCP provides $\Omega_E$ at zenith, $\Omega_E(0)$. b$L_e$ was measured from LAI-2000 and $L_t$ was quantified using litterfall $L$ and DCP based $W$. cDCP-LAI2000 uses $L_e/L_t$ relation by using indirect methods; $L_e$ measured from LAI-2000 and $L_t$ measured from DCP. CC indicates Chen and Cihlar (1995) method. CLX is the combination of LX (Lang and Xiang 1986) and CC methods (Leblanc et al. 2005). DHP is digital hemispheric photography, DCP is digital cover photography, and TRS is traversing radiometer system.

<table>
<thead>
<tr>
<th>Method</th>
<th>$\Omega_E$</th>
</tr>
</thead>
<tbody>
<tr>
<td>TRAC</td>
<td>0.69±0.07 (CLX)</td>
</tr>
<tr>
<td>DHP</td>
<td>0.57±0.01 (CLX)</td>
</tr>
<tr>
<td>DCP</td>
<td>0.69±0.05</td>
</tr>
<tr>
<td>TRS</td>
<td>0.61 (CLX)</td>
</tr>
<tr>
<td>Nilson (1999)</td>
<td>0.54</td>
</tr>
<tr>
<td>Kobayashi and Iwabuchi (2008)</td>
<td>0.54</td>
</tr>
<tr>
<td>$L_e/L_t$</td>
<td>0.49±0.02</td>
</tr>
<tr>
<td>DCP-LAI2000</td>
<td>0.49±0.10</td>
</tr>
</tbody>
</table>

The angular dependence of $\Omega_E$ was tested using TRS, TRAC measurements and three theoretical approaches (Figure 2.4). Based on the TRS data, $\Omega_E$ decreased with increasing $\theta$ (linear regression, $r^2=0.15$, $p<0.01$) (Figure 2.4a). On the range between 40 to 70° ($\theta$), $\Omega_E$ in the morning were significantly lower than those in the afternoon for CLX whereas there was no significant difference in CC method. In the morning, big gaps were pronounced whereas incoming PAR fluctuated more in the afternoon (subplot in Fig 4a). TRAC showed that $\Omega_E$ decreased with $\theta$ for both CLX and CC methods (linear regression, $r^2=0.21$, $p=0.05$ for CLX, $r^2=0.72$, $p<0.01$ for CC) (Figure 2.4b). Nilson (1999), Kobayashi and Iwabuchi (2008) and inversion of Eq. 2.8 showed that $\Omega_E$ decreased with $\theta$ (linear regression, $r^2=0.89$, $p<0.001$ for Nilson (1999), $r^2=0.98$, $p<0.0001$ for Kobayashi and Iwabuchi (2008), $r^2=0.94$, $p<0.01$ for inversion of Eq. 2.8). DHP-derived $\Omega_E(\theta_v)$ was not used in testing the angular dependence of $\Omega_E$ because in 30% of the photographs no leaves were present from 0 to 60° of $\theta_v$ due to canopy openness, resulting in undefined $\Omega_E$. 

18
Figure 2.4. (a) Element clumping index ($\Omega_E$) with solar zenith angle measured from a traversing radiometer system (DOY207, 209 and 211). All data were grouped into 10 degree intervals, and each point represents their mean over three days of measurements. CLX indicates $\Omega_E$ from the corrected Lang and Xiang (1986) method (Leblanc et al. 2005). CC indicates $\Omega_E$ from Chen and Cihlar (1995) method. The sub-box plot (Fig 3.a) indicates raw incoming photosynthetically active radiation (PAR) data measured from the tram on DOY 209. Within the sub-box plot, red dashed lines indicate 40 and 70° $\theta$. (b) Element clumping index ($\Omega_E$) with view zenith angle measured from a TRAC sensor, Nilson 1999, Kobayashi and Iwabuchi 2008, inversion calculation from Eq. 2.8, and DCP.
2.4.4. Woody area index
We quantified $W$ using DCP and Nilson (1999). The $W$ quantified by DCP was 0.32±0.08. The estimation of Nilson (1999) was 0.24 and 0.05 for $B$ and $T$, respectively, resulting in $W$ equal to 0.29, which was not significantly different from the DCP estimate ($p>0.05$). We chose the DCP-based estimate of $W$ because of the associated uncertainty.

2.4.5. Leaf area index
The comparison of $L_e$ among six methods is presented in Figure 2.5a. The $L_e$ derived from DHP was significantly lower than that from LAI-2000. TRAC showed the largest uncertainty of $L_e$. DCP provided $L_e$ at zenith direction, thus it is not comparable with the other methods. Indirect estimates of $L$ converted from $L_e$ by considering $W$ and $\Omega_E$ are given in Figure 2.5b. Among indirect estimates of $L$ that reported uncertainty, only DHP (CLX and CC) was significantly different from litterfall and allometry ($p<0.05$). We did not calculate LAI-2000 based $L$ because our best estimate of $\Omega_E$ used $L_e/L_i$ relation where $L_e$ was derived from LAI-2000, thus this way causes circularity fallacy to calculate $L$. 
Figure 2. 5. (a) Effective leaf area index ($L_e$) comparison among LAI-2000, DCP, DHP, TRAC, TRS and Nilson (1999). DCP provided $L_e$ at zenith direction. (b) Leaf area index ($L$) comparison among litterfall, allometry, DHP, DCP, TRAC and RTS. CC indicates $L$ calculation using $\Omega_E$ derived from Chen and Cihlar (1995). CLX indicates $L$ calculation using $\Omega_E$ derived from combination of Chen and Cihlar (1995) and Lang and Xiang (1986) method (Leblanc et al. 2005). DCP is digital cover photography, DHP is digital hemispherical photography, and TRS is traversing radiometer system. Error bars indicate 95% confidence interval.

2. 4. 6. Minimum sample size and plot size
We estimated the minimum sample size and plot size to obtain spatially representative $P_o$ and $L_e$ within the 300×300 m area based on the gridded LAI-2000 measurements (Figure 2. 1a). The minimum sample size to obtain 5% CV for each ring’s $P_o$ was 38, 35, 34, 42 and 63 (Figure 2.
The CV of 5\textsuperscript{th} ring was significantly higher than the other rings ($p<0.05$). The CV of $L_e$ decreased with plot size, and 240×240 m plot size was necessary to obtain 5\% CV (Figure 2. 6b).

![Graph](image)

Figure 2. 6. (a) Coefficient of variation (CV) for mean gap fraction at each view zenith angles in LAI-2000 with sampling numbers. Dashed line indicates 5\% of CV. (b) Coefficient of variation of $L_e$ measured from LAI-2000 with window size within the 300×300 m area (Fig 2. 1a).

2. 5. Discussion
Characterizing $L$ in savannas has remained challenging because most indirect methods assume homogeneous, open canopies. Our results from two direct and five indirect methods and two models demonstrated that a thorough evaluation of $P_o$ between various methods is an essential prerequisite. The pronounced canopy openness and heterogeneity at our site is characterized by low $\Omega_E$, and large sampling number and extensive plot size that are required to get spatially representative $L_e$. This result highlights the importance of clumping effect at the ecosystem scale to estimate $L$ adequately in the heterogeneous ecosystem. In the following sections, we answer the questions and provide support in favor or against the hypotheses addressed.

2. 5. 1. What are the strengths and weaknesses of multiple methods to assess $L$ in heterogeneous, open canopies?

Among indirect instruments, LAI-2000 was the only one to quantify $P_o$ over a wide range of $\theta$, reliably (Figure 2. 3a). This result lends credence to the use of LAI-2000 to acquire spatially representative $P_o(\theta)$, and consequently $L_e$ in heterogeneous ecosystem. The conversion of $L_e$ to $L_t$ by LAI-2000 itself may be possible by using LX method (i.e. $\ln(P_o(\theta))$) (Lang and Xiang 1986). The ratio of $L_e$ calculated from $\ln(P_o(\theta))$ to $L_e$ calculated from $\ln(P_o(\theta))$ was $0.82\pm0.04$. That is, to some degree, LX method considered clumping effect, yet it was still significantly higher than our best estimate $\Omega_E$ ($0.49\pm0.02$) ($p<0.05$). Therefore, independent $\Omega_E$ must be quantified and applied to LAI-2000 to convert $L_e$ to $L_t$. Based on our results, however, no independent method provided reliable $\Omega_E$ compared to $L_e/L_t$ (Table 3), thus the conversion of $L_e$ to $L_t$ in LAI-2000 remains a main challenge in this oak-savanna site.

The DCP provided reliable $P_o$ at zenith. Because of high image resolution and short path length (zenith direction), DCP could identify very small leaves and gaps (Figure 2. 7a), which gave very accurate $P_o(0)$ (Figure 2. 3a). Other important strengths of DCP are its ability to quantify $\Omega_E$ at zenith and $W$, which were reliable compared to other methods (see 4.3 and 4.4). Thus, DCP can quantify $L$ by itself if $\Omega_L$ is given. However, it does not have capacity to determine canopy structure over a wide range of $\theta$ by only measuring zenith direction. Also, its narrow view angle produced wide error bar (Figure 2. 5). Comparing DHP that had same sample size (47), 95% CI of DCP was three times greater than that of DHP. Thus, to apply DCP in open canopies, a large sample number is required. Due to the simplicity of DCP measurements that can be made during daylight hours (Macfarlane et al. 2007b), we do not consider the large sample number as a limitation.

The DHP overestimated $P_o$ and underestimated $L$ when compared to the litterfall $L$. Because of the large number of samples and the large footprint covered by DHP, the 95% CI of $L$ was smallest among all the indirect methods. Specifically, $P_o$ over 40 to $70^\circ$ $\theta$, was significantly higher than other direct and indirect methods (Figure 2. 3a). A critical limitation of DHP to obtain accurate $P_o$ estimates in this ecosystem is that the short focal distance of the fish eye lens causes image chromatic aberration especially at angles larger than $60^\circ$ (Frazer et al., 2001). This limitation is critical in ecosystems with open canopies because the most important $P_o$ information is found at those angles (Figure 2. 7b). Adequate determination of light exposure is also challenging in open canopies. We followed the protocol proposed Zhang et al. (2005) on the
determination of light exposure as developed in boreal forests covering a wide range of $L_e$ (0.2 to 5). Even if this protocol was evaluated at very low $L$ sites, tree distribution at boreal forests is assumed to be different from savannas where trees form clusters and open spaces prevail. In savannas, the canopy openness of the $P_o$ measurement position could be similar with that of the sky reference position, thus attention must be paid in determining diaphragm aperture to avoid over exposure of the image. An important strength of DHP is that this method averages $P_o(\theta_v)$ over a 360° azimuthal direction and a wide range of $\theta_v$, which reduces spatial variability. Finally it is important to consider that the wide spatial average of $P_o(\theta_v)$ using DHP compromises the calculation (underestimation) of $L$ by missing critical information at angles larger than 60°.
The TRAC and TRS had a weakness of its limited field-of-view by using the direct radiation beam. We believe that the gap size distribution function employed in TRAC and TRS correctly estimated $P_o$ (Figure 2.3b) but due to small transect numbers, the $P_o$ did not represent the spatial heterogeneity (Figure 2.6a). It is notable that 95% CI of TRAC based $L$ was largest among the seven methods. To overcome the insufficient footprint of TRAC measurement, large sample size is required. However, it will take much time to use TRAC at many transects over a wide range of $\theta$ because sun fleck size measurement requires very slow walking speed (~0.3 m s$^{-1}$) (Leblanc et al. 2002). RTS had strengths by keeping the sensor speed constant and the sensor leveled, yet due to one sampling transect caused by rail track structure, the quantification of 95% CI on $L$ was not available. Thus, the use of TRAC and TRS may be impractical to obtain spatially representative $P_o$, $L_o$ and $L_t$ in such a heterogeneous landscape.

The litterfall method provides a direct estimate of $L$. It is a straightforward approach that is primarily limited by sample size. Relative to the indirect approaches, collecting litterfall takes a great deal of time. Moreover even with a dedicated effort to maintain 25 collectors, we sampled a very small percentage of the total area (0.02%) due to limited resources to analyze litterfall data. We were forced to keep the size of our opening small (on average 0.16 m$^2$) to restrict access by the cattle that grazed this site. As a consequence in heterogeneous ecosystems like this oak savanna, there is a great deal of spatial variation. Indeed, the differences among collectors accounted for 96% of the observed uncertainty in the estimate of litterfall $L$. The litterfall plot
was one quarter of the LAI-2000 plot size. We compared $P_o(\theta)$ of five rings in LAI-2000 between the litterfall plot area and the other area, and we did not find significant difference ($p>0.05$). Thus we assumed that litterfall $L$ value can represent the LAI-2000 plot area.

In contrast there was very little statistical uncertainty associated with allometric $L$ because there was no sampling error. All of the trees within the 150 $\times$ 150 m plot were measured. The confidence intervals were based on propagating the errors associated with projections of the 2008 tree diameters and with the allometric relationship between leaf area and tree diameter reported by Karlik and McKay (2002). However Karlik and McKay (2002) measured blue oak trees in southern California, 280 km from our site. We do not know if or by how much blue oak allometry varies across its range.

2.5.2. How to estimate spatially representative clumping index in savannas?

The accurate estimation of $\Omega_E$ was very critical to convert $L_c$ to $L_I$ in this savanna site. We determined spatially representative $\Omega_E$ at the ecosystem scale to be 0.49±0.02, which is the lowest value reported so far. It indicates that the clumping effect was dominant at the between-crown scale that corresponds with the open nature of savannas. It is notable that the $\Omega$ values at boreal coniferous trees are comparable with the value at this site, yet boreal coniferous trees were highly clumped at shoot level and less clumped between crowns level (e.g. $\gamma=1.6$, $\Omega_E=0.92$ of black spruce) (Chen et al. 2006). In spite of the importance of $\Omega_E$ to quantify $L$ properly, the methodology to quantify spatially representative $\Omega_E$ in savannas has been less explored. Only one study used the TRAC instrument to quantify $\Omega_E$ in African savannas (Privette et al. 2004).

We used several instruments including TRAC, TRS, DCP and DHP to quantify $\Omega_E$, yet all instruments did not provide spatially representative $\Omega_E$. TRAC (n=4) and TRS (n=1) covered only a small portion of study area whose canopy structure is different from the whole study area as proved by $P_o$ comparison (Figure 2.3a). Thus, TRAC and TRS based $\Omega_E$ will represent only some local areas and they were significantly different from our best estimate. DCP provided $\Omega_E$ only at zenith, thus integral of $\Omega_E$ over the hemisphere was not possible. DHP overestimated $P_o$ over 40 to 70° $\theta_v$, thus its calculation of $\Omega_E$ is unreliable because $P_o$ is a key input parameter to calculate $\Omega_E$ when using gap size distribution function (Chen and Cihlar 1995a; Leblanc 2002). DHP (CLX) based $\Omega_E$ was not significantly different from our best estimate ($p>0.05$), but it is unclear whether it was by correct derivation or by artifact. This analysis highlights that enough sample size and adequate performance of the instruments must be made to get spatially representative $\Omega_E$.

Besides sampling area and performance of instruments, the calculation of $\Omega_E$ (i.e. CLX vs CC) needs further investigation to acquire spatially representative $\Omega_E$. The $\Omega_E$ calculated from the CLX method was significantly lower than that from the CC method (Table 3). Also, the $\Omega_E$ calculated from the CLX method was 0.23 lower than the CC method in 29 boreal forests (Leblanc et al. 2005). Leblanc et al. (2005) advocated the CLX method because it gave a closer $L$ value to the allometry based $L$ estimate. However, in a thinning experiment conducted at an eucalyptus forest, it was reported that $G(\theta)$ changed with thinning whereas $\Omega$ did not change in the CLX method, which is hard to explain (Macfarlane et al. 2007b). Here we tested both methods using the TRS data (Figure 2.4a). Theoretically, frequent big gaps should lead to lower $\Omega_E$ values (Kucharik et al. 1999). Only CLX method presented significantly lower $\Omega_E$ in the
morning when frequent big gaps prevailed than afternoon (Figure 2. 4a). Both CC and CLX methods remove large gaps within each segment that can not appear in randomly distributed leaves using the CC method; if the reduced gap size distribution function is still not random after removing the large gaps, then only the CLX method accounts for non-random gaps using the Lang and Xiang (1986) method (Leblanc et al. 2005). Therefore, we support the CLX method which is based on both theoretical and experimental considerations. Because most studies employing TRAC sensor have used the CC method, special attention is required when using $\Omega_\varepsilon$ values from the literature.

In this study, we determined spatially representative $\Omega_\varepsilon$ using $L_\varepsilon/L_t$ relation. There is a criticism on the derivation of $\Omega_\varepsilon$ using $L_\varepsilon/L_t$ because the multiple-scattering of light in the canopy at high $\theta_\varepsilon$ can cause erroneous $L_\varepsilon$ estimate from the LAI-2000 instrument (Chen et al. 1997). However, we believe this is not the case in this savanna site because $P_o(\theta)$ measured from the LAI-2000 was reliable even at the highest $\theta_\varepsilon$ (Figure 2. 4). We presume that the frequent open space with low $L$ may avoid serious contamination of $P_o$ by the multiple-scattering of light. We confirmed the reliability of $\Omega_\varepsilon$ calculated from $L_\varepsilon/L_t$ by comparing with the values of $\Omega_\varepsilon$ derived from two $P_o$ models (Table 3). In heterogeneous savannas, $L_\varepsilon/L_t$ method may be adequate way to acquire spatially representative $\Omega_\varepsilon$. We suggest combining LAI-2000 (for $L_\varepsilon$) and DCP (for $L$ and $W$) to get spatially representative $\Omega_\varepsilon$ indirectly (DCP-LAI2000 in Table 3). This indirect approach gave 0.49±0.10, which was not significantly different from $L_\varepsilon/L_t$ using litterfall $L$. This approach may be used to validate satellite based regional $\Omega$ map that calculated $\Omega_\varepsilon$ based on $L_\varepsilon/L_t$ relation (Chen et al. 2005).

2. 5. 3. Angular dependence of element clumping index

Based on two instruments (TRAC and TRS), two $P_o$ models and an inversion calculation of Eq 2. 9 (Figure 2. 3), we found that $\Omega_\varepsilon$ decreased with $\theta$ thus we rejected the first hypothesis where the element clumping index may increase with $\Omega_\varepsilon$.

Several papers reported that $\Omega_\varepsilon$ values change with $\theta$ (Andrieu and Sinoquet 1993; Chen 1996; Chen et al. 2008; Kucharik et al. 1999; Norman and Welles 1983) yet the underlying mechanism is still unclear. Previous studies from several boreal needle-leaved forests reported that $\Omega_\varepsilon$ increased with $\theta$ (Chen 1996; Kucharik et al. 1999; Leblanc et al. 2005) and oak and maple trees (Kucharik et al. 1999), which is in contrast to our finding. This trend may be explained by the gap size distribution (Chen 1996). When canopies are horizontally dense and vertically prolonged, the path length of a ray through the canopies increases with $\theta$. The longer path length makes large gaps be decomposed into smaller ones, which is close to random gap size distribution (close to 1 of $\Omega_\varepsilon$). However, this explanation needs to be tested in heterogeneous landscape.

We analyzed the factors influencing the angular dependence of $\Omega_\varepsilon$ (Eq. 2. 16). The angular trends of $\Omega_\varepsilon$ with $\theta_\varepsilon$ could be caused by factors on leaf, crown and tree distribution pattern levels. We found that the angular dependence of $\Omega_\varepsilon$ was modulated to some degree by ecosystem scale tree distribution patterns, rather than by leaf and crown level. First, in the leaf level, $f(\theta_\varepsilon)$ could be considered as a potential factor to modulate $\Omega_\varepsilon$ as influencing gap size and $P_o$ through its influence on the $G$ in Eq. 2. 16. Just the erectophile type of leaf angle distribution could cause a decrease in $\Omega_\varepsilon$ along with the view angle $\theta_\varepsilon$. However, the measured $f(\theta_\varepsilon)$ was not far from
spherical distribution, which indicates angular dependence of $\Omega_E$ on $f(\theta_L)$ will be marginal. Second, at the crown level, the crown shape was practically spherical and thus the product $S(\theta_L)\cos \theta_v$ in Eq. 2.16 was nearly constant with respect to $\theta_v$. Therefore, angular dependence of $\Omega_E$ should not much be caused by crown shape. Lastly, the next factor that possibly causes the angular dependence of $\Omega_E$ is the tree distribution pattern at ecosystem scale, if the pattern is different when the forest is viewed at different angles. In Eq. 2.16 the tree distribution pattern effect is characterized by the factor $c(\theta_v)$ which is mainly determined by the relative variance of the number of trees occurring on a subplot whose area is equal to the projection area of the crown envelope (Eq. 2.14). A potential dependence of the single-crown gap fraction $P_1(\theta_v)$ (Eq. 2.15) on the view angle $\theta_v$ is marginal because of spherical crown form and close to spherical leaf orientation. If looking at a sphere at different angles, the path length inside a spherical crown does not depend on the angle. If the trees are regularly spaced, the $\Omega_E$ is large. If the trees show a clumped distribution pattern, the $\Omega_E$ is smaller. Based on the distribution of tree numbers occurring on a circular subsample of given area (Figure A2.1 in Appendix 2.2), the distribution pattern when viewed at near-zenith angles showed a slightly regular pattern up to the angles 8, 22, 37 and 52°. It was close to random at 67° and showed a clumped distribution at 82°. In the vertical view, the pattern seems to be regular because of certain repulsion effect in the pattern. It is notable that trees cannot grow too near to each other. Even if the trees seem to grow in clusters, there seems to be a regular displacement of trees within a cluster. At larger plot sizes corresponding to large view angles (82°), the clustered character of the pattern started to come out, thus giving rise to an increase of the relative variance $GI$ and a decrease of $c(\theta_v)$ in Eq. 2.16 and $\Omega_E$ along with the view angle $\theta_v$. A closer observation at the site map (Figure 2.1a) shows that there are large gaps with no trees surrounded by tree-dense regions. Therefore, we believe that the angular dependence of $\Omega_E$ was controlled by ecosystem scale tree distribution patterns to some degree. We suggest that the angular dependence of $\Omega_E$ on the ecosystem scale tree distribution might be a unique characteristic in heterogeneous savanna ecosystem.

2.5.4. Influence of gaps between crowns on total gap fraction

Based on Nilson (1999) model simulation, we found that gaps between crowns at the oak-savanna site dominantly influenced total $P_o$ compared to three other species from sub-boreal region (Figure A.2 in Appendix 2.3). This result is consistent with lower $\Omega_E$ at the study site because gaps between crowns dominantly cause the gap size distribution function to deviate from random (Kucharik et al. 1999). Because on average 60% of total gaps were derived from between crowns gaps (Appendix C), indirect instruments actually measured $P_o$ that is not related with canopies, indicating that the accurate quantification of $\Omega_E$ is most important to quantify $L$ in this oak-savanna ecosystem. This simulation analysis highlights the dominance of frequent open spaces in the savanna, thus we support our second hypothesis where the influence of gaps between crowns on total $P_o$ may be dominant in the savanna site.

2.6. Summary and conclusions

In this study, we quantified tree $L$ using assessments of the probability of beam penetration made with multiple instruments and multiple gap fraction models in a heterogeneous oak-savanna ecosystem. We demonstrated pronounced heterogeneity at the study site; this was supported by low $\Omega_E$ (0.49), large proportion of between-crown gaps (60%), and large minimum sample (63) and plot size (5.8 ha) to obtain spatially representative values of $L_o$ at ecosystem scale. The
application of indirect methods in heterogeneous ecosystems such as savannas has been less explored. To acquire spatially representative $L$ and its associated canopy structure variables, we suggest following procedure:

1. Characterize $f(\theta_L)$ to quantify $G$-function.
2. Use DCP to estimate $P_\theta(0)$, $\Omega_E(0)$, $L_0$, and $W$ to quantify $L$.
3. Use LAI-200 to quantify $P_\theta(\theta_V)$ and $L_e$.
4. Estimate $\Omega_E$ at ecosystem scale using $L_e/L$ relation.
5. Characterize $\Omega_E(\theta_V)$ using inverse calculation of Eq. 2.

One digital camera that is able to resolve individual leaves as a function of leaf size and distance from tower to the trees-of-interest can be used to quantify $f(\theta_L)$ (our horizontal view digital camera method) and $L$(DCP method) with confidence in savannas. In-detail canopy structure information may be extracted by combining DCP and LAI-2000. This approach needs to be evaluated at other ecosystems. The use of TRAC and DHP in heterogeneous savannas calls special attention because of the limited footprint covered by the sensor (TRAC) and chromatic aberration at high $\theta_V$ with a difficulty to determine light exposure (DHP). To apply TRAC and DHP adequately, their $P_\theta(\theta_V)$ must be evaluated first with the LAI-2000 or other gap-fraction models. Our results highlight the importance of ecosystem-scale clumping effects for the adequate quantification of tree $L$ in savannas. Furthermore, we showed that the modeling-measurement integration approach was essential to understand canopy structure and light penetration in this oak-savanna ecosystem.
Chapter 3: On the correct estimation of effective leaf area index

3. 1. Introduction

Effective leaf area index ($L_e$) is defined as the product of the clumping index ($\Omega$) (Nilson 1971) and the leaf area index ($L$) (Black et al. 1991). Thus, $L_e$ assumes no foliage clumping given the gap fraction ($P_o$) relating to the probability of beam penetration through the canopies. This definition is straightforward for one sample, but it is unclear for multiple samples across a heterogeneous and clumped canopy. So far, there has been little attention on the consistent use of $L_e$ in spite of its importance to obtain $L$ adequately.

Miller’s theorem (Miller 1967) has traditionally been used to quantify $L_e$ (Chason et al. 1991; Welles and Norman 1991). The theorem integrates the logarithm of $P_o$ (Eq. 3. 1) over the range of view angles. For multiple samples, the method used to average $P_o$ needs careful attention because two averaging methods ($\ln P_o(\bar{\theta})$ vs $\ln P_o(\tilde{\theta})$) exist (Lang and Xiang 1986) and consequently there are many circumstances when they provide different $L_e$ estimates. The two approaches assume a random distribution of leaves in space within the sampling domain ($\ln P_o(\bar{\theta})$) and within the sensor’s field-of-view ($\ln P_o(\tilde{\theta})$). Thus, one could hypothesize that the latter approach provides an estimate closer to $L$ since clumping effects are partially considered at scales larger than the shoot (Lang and Xiang 1986).

The LAI-2000 Plant Canopy Analyzer (Li-COR, Nebraska, NE, USA) has been routinely used to quantify $L_e$ (Chen et al. 2006; Smolander and Stenberg 1996), yet few studies have explored how to estimate $L_e$ consistently using the LAI-2000 instrument. Researchers have mainly used the software provided by the vendor (i.e., C2000.exe or FV2000.exe) to post-process LAI-2000 measurements. The software calculates $L_e$ using the $\ln P_o(\bar{\theta})$ averaging method (Welles and Norman 1991), which potentially incorporates clumping effects (Fassnacht et al. 1994). The combination of LAI-2000 and Tracing Radiation and Architecture of Canopies instrument (TRAC; 3rd Wave Engineering, ON, Canada) has been proposed to quantify $L_e$ and clumping at scales larger than the shoot, combined with independent destructive estimates of clumping within shoot (e.g. conifers) to estimate $L$ (Chen et al. 2006). Thus, separating clumping effects from $L_e$ is critical to quantify $L$ correctly.

The information on the spatial distribution of leaves ($\Omega$) is crucial to model canopy photosynthesis (Baldocchi and Harley 1995; Baldocchi and Wilson 2001; Norman and Jarvis 1974, 1975) and radiative transfer accurately (Acock et al. 1970; Baldocchi et al. 1985; Baldocchi et al. 1984; Norman and Welles 1983), yet most land surface models have not incorporated this information. Though there have been some pioneering efforts to map clumping

---

2 This chapter is reprinted, with permission, from the original journal article: Ryu, Y., Nilson, T., Kobayashi, H., Sonnentag, O., Law, B.E., & Baldocchi, D.D. (2010). On the correct estimation of effective leaf area index: Does it reveal information on clumping effects? Agricultural and Forest Meteorology, 150, 463-472
factors globally (Chen et al. 2005), our understanding of $\Omega$ is still limited due to the difficulty in quantifying $\Omega$ from field-based measurements. For example, Ryu et al. (2010) reported that three instruments (TRAC, digital hemispheric photography, and traversing radiometer system) showed significantly different $\Omega$ values in an open savanna ecosystem. Also, clumping effects appear at multiple scales from shoot level (Chen 1996; Norman and Jarvis 1974, 1975), between-crown level (Kucharik et al. 1997; Nilson 1999), and ecosystem level, such as savannas (Ryu et al. 2010). The multi-scale nature of clumping effects makes it hard to quantify $\Omega$ correctly. Thus, quantifying and understanding spatial and temporal variability of the upper limit of $\Omega$ will be useful to constrain and characterize $\Omega$ correctly.

In this study, we focus on $L_e$ instead on $L$ because quantifying $L_e$ using optically based indirect methods is the first step to estimate true $L$. The accurate estimation of $L_e$ will help to constrain $\Omega$ as well. The goal of this study is to investigate the correct estimation of $L_e$. The scientific questions include: 1) which $P_o$ averaging method results in theoretically consistent $L_e$? 2) If two methods give different $L_e$ estimates, what causes these differences? 3) To what degree are clumping effects captured by LAI-2000 measurements? and 4) How can LAI-2000 derived clumping effects be used to constrain the true clumping index in a spatial and temporal context? We address these questions through theoretical considerations, a forest gap-fraction model (Nilson 1999; Nilson and Kuusk 2004), and raw LAI-2000 data surveyed across a range of vegetation types collected from 41 sites.

3.2 Methods and Materials

3.2.1 Theory

Monsi and Saeki (1953; 2005) proposed the $P_o$ theory. Under certain conditions, the probability of beam penetration can be described by the Poisson distribution:

$$P_o = \exp\left(-L_e G(\theta) / \cos \theta \right) = \exp\left(-\Omega \theta G(\theta) / \cos \theta \right)$$

(3.1)

where $G$ is the leaf projection function (Warren Wilson 1960) and $\theta$ is the view zenith angle. For simplicity, woody material is ignored as leaves tend to present themselves to obscure underlying stems from sun (Kucharik et al. 1998b). Miller (1967) proposed a theorem for the inverse estimation of $L_e$ that does not require a prior knowledge of the $G(\theta)$:

$$L_e = 2 \int_{0}^{\pi/2} \left[-\ln P_o(\theta) \right] \cos \theta \sin \theta \, d\theta$$

(3.2)

For multiple samples, $L_e$ can be derived by two slightly different approaches (Lang and Xiang 1986):

$$L_e = 2 \int_{0}^{\pi/2} \left[-\ln \overline{P_o}(\theta) \right] \cos \theta \sin \theta \, d\theta$$

(3.3)

$$L_e = 2 \int_{0}^{\pi/2} \left[-\ln \overline{P_o}(\theta) \right] \cos \theta \sin \theta \, d\theta$$

(3.4)
We define the ratio of Eq. 3.3 to Eq. 3.4 to be an “apparent” clumping index ($\Omega_{\text{app}}$):

$$\Omega_{\text{app}} = \frac{1}{2} \int_0^{\pi/2} \frac{\ln P_o(\theta)}{\cos \theta \sin \theta} \cos \theta \sin \theta \, d\theta$$

(3.5)

$\Omega_{\text{app}}$ is always less than 1 because of the convexity of the logarithmic function. Thus, the greater the degree of clumping, the lower $\Omega_{\text{app}}$. Eq. 3.5 follows the definition of $\Omega$ by using the ratio of measured $L_e$ to approximated $L$ as used in the previous studies (Leblanc et al. 2005; van Gardingen et al. 1999).

To characterize $\Omega_{\text{app}}$ using a forest gap fraction model (Nilson 1999; Nilson and Kuusk 2004), we apply second order Taylor’s expansion:

$$-\ln P_o(\theta) \approx -\ln P_o(\theta) - \frac{1}{2} (\ln P_o(\theta))^2 \text{Var}(P_o(\theta))$$

(3.6)

which includes the second derivative of logarithm and the variance of gap fraction ($\text{Var}(P_o(\theta))$). Taking the second derivative of logarithm ($-1/(\ln P_o(\theta))^2$) and integrating Eq. 3.6 over the zenith angle we obtain

$$\int_0^{\pi/2} -\ln P_o(\theta) \cos \theta \sin \theta \, d\theta \approx \int_0^{\pi/2} -\ln P_o(\theta) \cos \theta \sin \theta \, d\theta + \frac{1}{2} \int_0^{\pi/2} \frac{\text{Var}(P_o(\theta))}{P_o(\theta)^2} \cos \theta \sin \theta \, d\theta$$

(3.6a)

We refer to the second term on the right hand side as a non-linearity correction term. The greater the variance of gap fraction at the view angle $\theta$, the greater non-linearity correction term. Then, $\Omega_{\text{app}}$ may be expressed as follows after rearrangement of Eq. 3.6a:

$$\Omega_{\text{app}} \approx 1 - 0.5 \int_0^{\pi/2} \frac{\text{Var}(P_o(\theta))}{P_o(\theta)^2} \cos \theta \sin \theta \, d\theta / \left[ \int_0^{\pi/2} -\ln P_o(\theta) \cos \theta \sin \theta \, d\theta \right]$$

(3.7)

The second term on the right hand side is a normalized- non-linearity correction term. The LAI-2000 instrument has no ability to measure $P_o$ at the shoot level, thus $\Omega_{\text{app}}$ (Eq. 3.5) does not consider clumping effects at the shoot level. Chen (1996) proposed the concept of the element clumping index ($\Omega_E$), which quantifies clumping effects at scales larger than the shoot level. Because $\Omega_{\text{app}}$ does not fully account the clumping effects at larger than shoot scale, it is expected that $\Omega_{\text{app}}$ is greater than $\Omega_E$.

### 3.2.2. Forest gap fraction model

By a forest gap fraction model (Nilson 1999; Nilson and Kuusk 2004), we can obtain the mean value and variance of between-crown $P_o(\theta)$ in forests. In particular, the variance of the gap fraction at a fixed angle $\theta$ and averaged over the azimuth (as in the LAI-2000 instrument) can be calculated. In model simulation of variance for a LAI-2000 ring, a $P_o(\theta)$ reading on a single LAI-2000 ring may be treated as an integral over the azimuth of a random function - gap probability at a fixed zenith angle. To calculate the variance of an integral of a random function, we need to know the autocorrelation function of gap probability, in our case along the azimuth at a fixed zenith angle. We use the Nilson and Kuusk (2004) model to describe the between-crown gap probability and its autocorrelation. For a binary (1: gap, 0: no gap) variable, the covariance ($\text{cov}(\theta, \phi)$) of the occurrence of gaps at two directions having the same $\theta$ but separated by the
azimuth difference $\phi$ can be calculated as
\[
\text{cov}(\theta, \phi) = P_{11}(\theta, \phi) d\phi - P_o^2(\theta)
\]  
(3. 8)

where $P_{11}(\theta, \phi)$ is the bi-directional gap probability that two lines of sight with the same view zenith angle $\theta$, but separated by the azimuth difference $\phi$, both occur in a between-crown gap. To calculate the variance of the gap fraction reading in a LAI-2000 ring, we have to calculate the double integral over the covariance function. Since the covariance is supposed to depend on the azimuth difference, only, the double integral is reduced to a single integral (Sveshnikov 1968). In Nilson and Kuusk (2004), the following formula was derived to calculate the variance of between-crown gap fraction averaged over the azimuth ring $\theta$:
\[
\text{Var}(P_o(\theta)) = \frac{2}{\pi^2} \int_0^\pi (\pi - \phi) P_{11}(\theta, \phi) d\phi - P_o^2(\theta)
\]  ,  
(3. 9)

Here, we have to note that this equation tends to somewhat underestimate the variance, since it assumes the variance of the integral over the azimuth from 0 to 2$\pi$ is two times of the same integral from 0 to $\pi$, thus ignoring the possible correlation between the two halves. However, all the qualitative effects should be adequately described by Eq. 3. 9. The calculation of $P_{11}(\theta, \phi)$ is reduced to finding the overlap area of two tree crown projections in the two directions. If these projections do not overlap, the respective covariance is zero. The larger the angular dimensions of crowns as viewed from the height of LAI-2000 measurements (especially diameter), the further extends the covariance along the azimuth and the greater the variance. The LAI-2000 can screen light in some portions of azimuthal range using various angular sizes of view caps. In principle, the model can consider the effect of view cap size in LAI-2000 measurements on the variance of $P_o(\theta)$, but we did not consider the use of view cap in the model throughout this manuscript.

The model requires input data including crown width, crown depth, canopy height, measurement height, tree distribution pattern and canopy cover. By changing the input data, it is possible to study the magnitude of the non-linear correction term and its dependence on canopy structures. For the simulation, we used input data as crown width (6-m), tree height (13-m) and measurement height (1-m). The tree distribution pattern was assumed to follow a Poisson distribution. We changed canopy cover (0.1, 0.2, … 0.9) by modulating tree density under the Poisson-distribution-based tree distribution pattern. We changed crown shape by modulating crown depth (1, 3, 6, 9, and 12-m) given the crown width. To explicitly consider between-crown gaps, we made crowns opaque by allocating high $L$ (e.g. 100).

### 3. 2. 3. Data

We compiled raw data from the LAI-2000 instrument at 41 sites that were distributed across six plant functional types ranging from tropical to boreal climatic zones (Table 3. 1). First, we calculated $P_o(\theta)$ at each location where a LAI-2000 reading was taken. Then, we applied the two $P_o(\theta)$ averaging methods (Eq. 3. 3 and 3. 4) and calculated $\Omega_{\text{app}}$ at each site. Independently-estimated element clumping index ($\Omega_E$), i.e. the clumping index at scales larger than shoots (Chen 1996), was available at 18 sites. The methods to calculate $\Omega_E$ include a gap size distribution model (Chen and Cihlar 1995a; Leblanc 2002), a forest gap fraction model (Nilson 1999; Nilson and Kuusk 2004), $\Omega_E$ model (Kucharik et al. 1999), and $L_c/L_t$ by direct measurements of both variables ($L_t$ is total plant area index) (Ryu et al. 2010). Since it is
practically impossible to separate the contribution of within-shoot gaps to the overall $P_o$, we compared $\Omega_{\text{app}}$ with $\Omega_E$ to investigate how much the LAI-2000 instrument could incorporate clumping effects. We performed paired t-tests between $\Omega_{\text{app}}$ and $\Omega_E$ within each plant functional type using JMP (SAS Institute Inc. v7.0, Cary, NC, USA).

3.2.4. Spatial scaling of apparent clumping index
To investigate the spatial scaling behavior of $\Omega_{\text{app}}$, we used the LAI-2000 raw data measured at Metolius, Oregon (Law et al. 2001b). At this site, LAI-2000 measurements were made on a systematic grid over twenty 100×100m plots. Each plot includes ~120 $P_o$ readings. The plots were distributed over a 10×15 km area to capture the range of variation in canopy structure over the landscape for a radar validation study; 18 of the plots were dominated by ponderosa pine and two contained primarily Douglas-fir. To study the impact of sample size (i.e. number of plots) on the calculation of $\Omega_{\text{app}}$, we selected sample sizes from 1 to 20. For each sample size, we followed the bootstrap technique and created 10,000 data sets by drawing random subsets of the respective size from all 20 plots without replacement (Efron and Tibshirani 1993). Then we calculated $\Omega_{\text{app}}$ for each sample size by averaging 10,000 resamplings.

3.3. Results and Discussion
3.3.1. Theoretically consistent $L_e$
We employed a simple theoretical model to investigate which $P_o$ averaging method provides a correct $L_e$ estimate (Figure 3.1). For the turbid media case (i.e. homogeneous canopy), there was no difference between the two $P_o$ averaging methods based on $L_e$ values (Figure 3.1a). However, for a clumped canopy, the two $P_o$ averaging methods resulted in different $L_e$ estimates (Figure 3.1b). As conceptualized in Figure 3.1b, the leaves are not randomly distributed due to a clumping effect caused by between-crown gaps (Nilson 1999). The $\ln P_o(\theta)$ method provided the true $L$ ($L=L_e=1$), indicating that this method incorporates clumping effects by locally applying the Poisson assumption (Lang and Xiang 1986). The $\ln P_o(\theta)$ approach quantifies $L_e$ correctly by assuming clumped leaves to be randomly distributed within the experimental domain. Thus, we confirm that the $\ln P_o(\theta)$ method must be used to estimate $L_e$, and the ratio of $L_e$ to $L$ (i.e. the clumping index) is 0.74. Consequently, we believe that the LAI-2000 software does not produce a theoretically consistent estimate of $L_e$, but it approximates true $L$ by incorporating clumping effects via the $\ln P_o(\theta)$ approach.
Figure 3.1. A conceptual diagram to calculate $L_e$. We assume direct beam originates from zenith direction (downward long arrows), leaf area index ($L$) in each crown is 2, there is no clumping within each crown, leaf inclination angle distribution is spherical (i.e. $G=0.5$ where $G$ is the leaf projection coefficient, Warren Wilson (1960)), and four measurements are taken as indicated by upward short arrows. $P_o$ is gap fraction. (a) A case of turbid media (homogeneous canopy). Two $P_o$ averaging methods give same result. (b) A case of clumped canopy. The vegetation cover fraction ($f_v=0.5$) and soil cover fraction ($f_{soil}=0.5$) are same. Two $P_o$ averaging methods give different results.
3.3.2. The effect of canopy structure on apparent clumping index

We used a theoretical \( P_o \) model (Nilson 1999; Nilson and Kuusk 2004) to investigate how LAI-2000 derived \( \Omega_{app} \) changes with crown shape, canopy cover and canopy height, which are important variables modulating clumping effects (Kucharik et al. 1999) (Figure 3.2). The simulated variance of \( P_o \) was the largest in the inner ring (ring 1) of the LAI-2000 instrument and monotonically decreased along with the view zenith angle (Figure 3.2a). The maximum variance of \( P_o \) occurred at around 0.4 of canopy cover (e.g., savannas) in the first ring while this maximum shifted towards lower canopy covers in the lower rings. The variance increased with vertically prolonged crown shape (Figure 3.2b). The non-linearity correction term and the normalized non-linearity correction term were found to be highest at higher canopy cover and vertically prolonged crown shapes (Figure 3.2c; d). \( \Omega_{app} \) was lower for prolate spheroids and greater for oblate spheroids. Generally, \( \Omega_{app} \) was greater where crown shape was spherical, resulting in similar path lengths at any view angles (Figure 3.2e). Another key factor in the \( \Omega_{app} \) is the angular size of the crown as seen from the height of measurements. For instance, in another numerical experiment tree height was assumed to be 26 m instead of 13 m (Figure 3.2f). The simulated \( \Omega_{app} \) values of the 13 m height were lower by ~0.04 than for the 26 m height. In taller canopies, the different view angles of the LAI-2000 instrument include more crowns, which cause the leaves to appear almost randomly distributed. Thus, we could expect that LAI-2000 derived \( \Omega_{app} \) is dependent on canopy architecture, including crown shape, canopy cover, and canopy height, as is \( \Omega_E \) (Kucharik et al. 1999). These results justify the use of \( \Omega_{app} \) to quantify clumping effects with respect to canopy structures.
Figure 3.2. (a) The relation between canopy cover and variance of gap fraction at each view zenith angles corresponding with LAI-2000 rings. (b)-(e) The relation between canopy cover,
crown shape and several variables in forest gap fraction model including (b) variance of gap fraction (Var in Eq. 3.6) averaged over the view angles weighted by \( \cos(\theta)\sin(\theta) \) where \( \theta \) is the view zenith angle, (c) non-linear correction term (\( NCT \) in Eq. 3.7), (d) normalized non-linear correction term (\( NCT_n \) in Eq. 3.7), and (e) apparent clumping index (\( \Omega_{\text{app}} \) in Eq. 3.7). All calculations are made with a gap fraction model (Nilson 1999; Nilson and Kuusk 2004) with input data of crown width (6-m), tree height (13-m) and measurement height (1-m). Tree distribution pattern is assumed to be Poisson distribution. Leaf area index is 100 to make crowns opaque to explicitly consider between-crown gaps. Canopy cover changes by modulating tree density. (f) The relation between apparent clumping index and canopy cover for different canopy height (13 m and 26 m). All other crown parameters are same with the above.

3.3.3 Clumping effects accounted for by the LAI-2000 instrument

We analyzed LAI-2000 raw data from 41 sites covering 8 plant functional types to investigate the degree of clumping accounted for by the LAI-2000 instrument (Table 3.1). Overall, \( \Omega_{\text{app}} \) was 0.90±0.08 (mean ± standard deviation) ranging from 0.60 to 0.99. It is notable that wheat and tall grass prairie sites where the LAI-2000 instrument was developed and tested (Welles and Norman 1991) showed \( \Omega_{\text{app}} \approx 1 \), implying closed, homogeneous canopies. The mean values of \( \Omega_{\text{app}} \) for each plant functional type ranged from 0.83 (mixed forest and woody savanna) to 0.96 (evergreen broad-leaved forest). The LAI-2000 instrument incorporated 35% (woody savanna site, Tonzi) to 100% of the clumping effects by comparison with independent \( \Omega_{E} \) estimates reported in the literature (Table 3.1). The combination of \( \ln P_{\theta}(\theta) \) averaging method derived \( L_\theta \) with independent \( \Omega_{E} \) estimates overestimated \( L \) up to 30% (Douglas-fir young forest).

We investigated the difference between \( \Omega_{\text{app}} \) and \( \Omega_{E} \) across diverse plant functional types (Figure 3.3). We found that there was no significant difference in evergreen needle-leaved forest, deciduous broad-leaved forest, mixed forest, and evergreen broad-leaved forest (\( p > 0.05 \), paired t-test) (Figure 3.3). We had only one sample at open shrub land and woody savanna which needed more sampling for statistical analysis. However, one woody savanna site (Tonzi ranch) showed a large discrepancy between \( \Omega_{\text{app}} \) (0.83) with \( \Omega_{E} \) (0.49). The discrepancy was expected because the assumption of randomly distributed leaves in space within each ring’s footprint is violated due to large spatial heterogeneity in savannas (Ryu et al. 2010). We recommend combining the LAI-2000 instrument and zenith direction digital cover photography to obtain correct \( \Omega_{E} \) in very heterogeneous canopies (Ryu et al. 2010).
Figure 3.3. Comparison of element clumping index between LAI-2000 derived method and independent estimate from literature (Table 3.1). Error bar indicates 95% confidence interval. Error bar appears only for the plant functional types whose sample size is greater than three. CRO: crop, DBF: deciduous broad-leaved forest, EBF: evergreen broad-leaved forest, ENF: evergreen needle-leaved forest, GRA: grass, MF: mixed forest, OSH: open shrub land, WSA: woody savanna.
Table 3.1. LAI-2000 raw data survey from 39 sites. $\Omega_{\text{app}}$ is clumping index derived from LAI-2000 gap fraction measurement (Eq. 3.5). $\Omega_{E}$ is element clumping index. DHP is digital hemispheric photography. TRAC is Tracing radiation and architecture of canopies. CC is clumping index calculated by Leblanc (2002). $L_{\text{e}}/L_{t}$ is the ratio of effective leaf area index to total leaf area index. CRO: crop, DBF: deciduous broad-leaved forest, EBF: evergreen broad-leaved forest, ENF: evergreen needle-leaved forest, GRA: grass, MF: mixed forest, OSH: open shrub land, WSA: woody savanna. aEarly planted, bLater planted, cOld Douglas fir, dYoung Douglas fir, eBlack spruce with many dead trees, fCC method that was not corrected by Leblanc (2002).

<table>
<thead>
<tr>
<th>Plant functional types</th>
<th>Country</th>
<th>Site</th>
<th>Latitude</th>
<th>Longitude</th>
<th>Climate</th>
<th>Species</th>
<th>$L_{\text{e}}$ (Eq 3.3)</th>
<th>$L_{t}$ (Eq 3.4)</th>
<th>$\Omega_{\text{app}}$</th>
<th>LAI-2000 data source</th>
<th>$\Omega_{E}$ from literature (method)</th>
<th>$\Omega_{E}$ source</th>
</tr>
</thead>
<tbody>
<tr>
<td>CRO</td>
<td>Japan</td>
<td>Nagaoka</td>
<td>37.49°N</td>
<td>138.78°E</td>
<td>Temperate</td>
<td>Rice$^a$</td>
<td>2.43</td>
<td>2.72</td>
<td>0.89</td>
<td>Kobayashi (unpublished data)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Japan</td>
<td>Nagaoka</td>
<td>37.49°N</td>
<td>138.78°E</td>
<td>Temperate</td>
<td>Rice$^b$</td>
<td>2.28</td>
<td>2.84</td>
<td>0.80</td>
<td></td>
<td>Kobayashi (unpublished data)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>USA</td>
<td>Ponca</td>
<td>city</td>
<td>36.45°N</td>
<td>97.05°W</td>
<td>Continental</td>
<td>Wheat</td>
<td>3.65</td>
<td>3.78</td>
<td>0.97</td>
<td>(Burba and Verma 2005)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>USA</td>
<td>Twitchell island</td>
<td>38.11°N</td>
<td>121.64°W</td>
<td>Mediterranean</td>
<td>Rice</td>
<td>5.21</td>
<td>5.56</td>
<td>0.94</td>
<td></td>
<td>This study</td>
<td></td>
<td></td>
</tr>
<tr>
<td>USA</td>
<td>Villinger</td>
<td>38.11°N</td>
<td>121.34°W</td>
<td>Mediterranean</td>
<td>Corn</td>
<td>0.31</td>
<td>0.39</td>
<td>0.79</td>
<td></td>
<td>This study</td>
<td></td>
<td></td>
</tr>
<tr>
<td>USA</td>
<td>Clements</td>
<td>38.20°N</td>
<td>121.09°W</td>
<td>Mediterranean</td>
<td>Grape</td>
<td>0.44</td>
<td>0.53</td>
<td>0.83</td>
<td></td>
<td>This study</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DBF</td>
<td>Estonia</td>
<td>Järvelåja</td>
<td>58.29°N</td>
<td>27.26°E</td>
<td>Boreal</td>
<td>Birch</td>
<td>3.65</td>
<td>3.75</td>
<td>0.97</td>
<td>VALERI project and (Kodar et al. 2008)</td>
<td>0.98 (Nilson and Kuusk 2004)</td>
<td></td>
</tr>
<tr>
<td>Italy</td>
<td>Roccarespampani 1</td>
<td>42.41°N</td>
<td>11.93°E</td>
<td>Mediterranean</td>
<td>Oak</td>
<td>3.28</td>
<td>3.70</td>
<td>0.89</td>
<td></td>
<td>(Tedeschi et al. 2006)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Italy</td>
<td>Roccarespampani 2</td>
<td>42.39°N</td>
<td>11.92°E</td>
<td>Mediterranean</td>
<td>Oak</td>
<td>4.42</td>
<td>4.57</td>
<td>0.97</td>
<td></td>
<td>(Tedeschi et al. 2006)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Japan</td>
<td>Takayama</td>
<td>36.14°N</td>
<td>137.42°E</td>
<td>Temperate</td>
<td>Oak</td>
<td>3.56</td>
<td>3.66</td>
<td>0.97</td>
<td></td>
<td>(Nasahara et al. 2008)</td>
<td>0.93 (CC, TRAC)</td>
<td>(Nasahara et al. 2008)</td>
</tr>
<tr>
<td>Korea</td>
<td>Gwangneung</td>
<td>37.76°N</td>
<td>127.15°E</td>
<td>Temperate</td>
<td>Oak</td>
<td>3.99</td>
<td>4.57</td>
<td>0.87</td>
<td></td>
<td>Kwon (unpublished data)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Country</td>
<td>Location</td>
<td>Latitude/Latitude</td>
<td>Vegetation Type</td>
<td>NCE-NEF</td>
<td>NCE-NEF</td>
<td>CC-TRAC</td>
<td>Notes</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>------------</td>
<td>----------------</td>
<td>--------------------</td>
<td>-----------------</td>
<td>----------</td>
<td>----------</td>
<td>----------</td>
<td>--------------------------------------------</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>USA</td>
<td>Coweeta</td>
<td>35.05° N 83.45° W</td>
<td>Temperate Oak-hickory</td>
<td>5.00</td>
<td>5.51</td>
<td>0.91</td>
<td>(Hwang et al. 2009)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>USA</td>
<td>Chestnut ridge</td>
<td>35.93° N 84.33° W</td>
<td>Temperate Oak</td>
<td>3.5</td>
<td>3.53</td>
<td>0.99</td>
<td>Heuer (unpublished data)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>USA</td>
<td>Walker branch</td>
<td>35.96° N 84.29° W</td>
<td>Temperate Oak</td>
<td>3.74</td>
<td>3.92</td>
<td>0.95</td>
<td>Heuer (unpublished data)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>USA</td>
<td>Harvard</td>
<td>42.54° N 72.17° W</td>
<td>Temperate Oak</td>
<td>4.81</td>
<td>5.19</td>
<td>0.93</td>
<td>(Urbanski et al. 2007)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EBF</td>
<td>Australia</td>
<td>32.61° S 116.03° E</td>
<td>Mediterranean Eucalyptus</td>
<td>1.62</td>
<td>1.69</td>
<td>0.96</td>
<td>(Macfarlane et al. 2007b)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>USA</td>
<td>Harvard</td>
<td>43.74° N 3.60° E</td>
<td>Mediterranean Oak</td>
<td>2.94</td>
<td>3.06</td>
<td>0.95</td>
<td>(Rambal et al. 2003)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Thailand</td>
<td>Kog-Ma</td>
<td>18.8° N 98.9° E</td>
<td>Tropical Lithocarpus</td>
<td>3.50</td>
<td>3.65</td>
<td>0.96</td>
<td>(Tanaka et al. 2008)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ENF</td>
<td>Canada</td>
<td>49.91° N 125.37° W</td>
<td>Boreal Douglas fir</td>
<td>3.57</td>
<td>3.88</td>
<td>0.92</td>
<td>(Chen et al. 2006)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Canada</td>
<td>Sandhill</td>
<td>53.80° N 104.62° W</td>
<td>Boreal Black spruce</td>
<td>2.54</td>
<td>2.75</td>
<td>0.93</td>
<td>Sonnentag (unpublished data)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Canada</td>
<td>Sandhill</td>
<td>53.80° N 104.62° W</td>
<td>Boreal Jack pine and black spruce</td>
<td>3.57</td>
<td>3.73</td>
<td>0.96</td>
<td>Sonnentag (unpublished data)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Estonia</td>
<td>Järvselja</td>
<td>58.30° N 27.26° E</td>
<td>Boreal Scots pine</td>
<td>2.57</td>
<td>2.61</td>
<td>0.99</td>
<td>VALERI project and (Kodar et al. 2006)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Estonia</td>
<td>Järvselja</td>
<td>58.30° N 27.26° E</td>
<td>Boreal Scots pine</td>
<td>2.57</td>
<td>2.61</td>
<td>0.99</td>
<td>This study</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes:
- CC: Canopy conductance
- TRAC: Transpiration ratio
- NCE-NEF: Net community exchange - net ecosystem exchange
- NEF: Net ecosystem exchange
- HWP: Hyperbolic water productivity
- EBF: Eastern Boreal Forest
- ENF: Eastern North American Forest
<table>
<thead>
<tr>
<th>Country</th>
<th>Location</th>
<th>Latitude</th>
<th>Longitude</th>
<th>Vegetation</th>
<th>LAI</th>
<th>σ</th>
<th>R²</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estonia</td>
<td>Järvselja</td>
<td>58.30°N</td>
<td>27.24°E</td>
<td>Boreal Spruce</td>
<td>3.05</td>
<td>3.12</td>
<td>0.98</td>
<td>VALERI project and (Kodar et al. 2008)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.95 (Nilson and Kuusk 2004)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>This study (Ryu et al. 2010)</td>
</tr>
<tr>
<td>Korea</td>
<td>Gwangneung</td>
<td>37.76°N</td>
<td>127.16°E</td>
<td>Temperate Pine</td>
<td>4.14</td>
<td>4.44</td>
<td>0.93</td>
<td>Kwon (unpublished data)</td>
</tr>
<tr>
<td>USA</td>
<td>Howland (Main)</td>
<td>45.20°N</td>
<td>68.74°W</td>
<td>Temperate Red spruce</td>
<td>3.92</td>
<td>4.09</td>
<td>0.96</td>
<td>Richardson (unpublished data)</td>
</tr>
<tr>
<td>USA</td>
<td>Howland (BlockA)</td>
<td>45.21°N</td>
<td>68.74°W</td>
<td>Temperate Red spruce</td>
<td>1.72</td>
<td>1.94</td>
<td>0.89</td>
<td>Richardson (unpublished data)</td>
</tr>
<tr>
<td>USA</td>
<td>US-NC2</td>
<td>35.48°N</td>
<td>76.40°W</td>
<td>Temperate Loblolly pine</td>
<td>3.94</td>
<td>4.23</td>
<td>0.93</td>
<td>(Noormets et al. 2009)</td>
</tr>
<tr>
<td>USA</td>
<td>Metolius</td>
<td>44.30°N</td>
<td>121.37°W</td>
<td>Temperate Douglas fir</td>
<td>0.99</td>
<td>1.27</td>
<td>0.78</td>
<td>(Law et al. 2001b)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.77 (CC, TRAC)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(Law et al. 2001b)</td>
</tr>
<tr>
<td>GRA</td>
<td>Canada Sandhill</td>
<td>53.79°N</td>
<td>104.62°W</td>
<td>Boreal Sedges</td>
<td>0.99</td>
<td>1.10</td>
<td>0.90</td>
<td>(Sonntenag et al. 2009)</td>
</tr>
<tr>
<td>USA</td>
<td>Sherman Island</td>
<td>38.04°N</td>
<td>121.75°W</td>
<td>Temperate Invasive weed</td>
<td>0.50</td>
<td>0.61</td>
<td>0.83</td>
<td>Sonntenag et al. (in preparation)</td>
</tr>
<tr>
<td>USA</td>
<td>Shidler</td>
<td>36.56°N</td>
<td>96.41°W</td>
<td>Continental Tallgrass</td>
<td>5.22</td>
<td>5.32</td>
<td>0.98</td>
<td>(Burba and Verma 2005)</td>
</tr>
<tr>
<td>USA</td>
<td>Twitchell island</td>
<td>38.11°N</td>
<td>121.65°W</td>
<td>Temperate Tule</td>
<td>4.45</td>
<td>5.24</td>
<td>0.85</td>
<td>This study</td>
</tr>
<tr>
<td>USA</td>
<td>Vaira</td>
<td>38.41°N</td>
<td>120.95°W</td>
<td>Temperate Grass</td>
<td>0.71</td>
<td>0.99</td>
<td>0.71</td>
<td>This study</td>
</tr>
<tr>
<td>MF</td>
<td>Canada Timmins</td>
<td>48.22°N</td>
<td>82.16°W</td>
<td>Boreal Aspen, Spruce, Birch, Fir</td>
<td>3.29</td>
<td>3.50</td>
<td>0.94</td>
<td>(Chen et al. 2006)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.93 (CC, DHP)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(Chen et al. 2006)</td>
</tr>
<tr>
<td>Estonia</td>
<td>Järvselja</td>
<td>58.29°N</td>
<td>27.25°E</td>
<td>Boreal Birch and Spruce</td>
<td>3.44</td>
<td>3.59</td>
<td>0.96</td>
<td>VALERI project and (Kodar et al. 2008)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.82 (Nilson and Kuusk 2004)</td>
</tr>
<tr>
<td>USA</td>
<td>Washington park</td>
<td>47.64°N</td>
<td>122.30°W</td>
<td>Mediterranean Fir, Maple</td>
<td>1.73</td>
<td>2.91</td>
<td>0.60</td>
<td>Richardson et al. 2009</td>
</tr>
<tr>
<td>Arboretum</td>
<td>Location</td>
<td>Mer Bleue</td>
<td>Latitude</td>
<td>Longitude</td>
<td>Zone</td>
<td>Species</td>
<td>Canopy Class</td>
<td>An</td>
</tr>
<tr>
<td>-----------</td>
<td>----------</td>
<td>-----------</td>
<td>----------</td>
<td>-----------</td>
<td>------</td>
<td>---------</td>
<td>--------------</td>
<td>----</td>
</tr>
<tr>
<td>OSH</td>
<td>Canada</td>
<td>Mer Bleue</td>
<td>45.4° N</td>
<td>75.5° W</td>
<td>Boreal</td>
<td>Evergreen shrubs</td>
<td>2.41</td>
<td>2.69</td>
</tr>
<tr>
<td>WSA</td>
<td>USA</td>
<td>Tonzi</td>
<td>38.43° N</td>
<td>120.97° W</td>
<td>Mediterranean</td>
<td>Blue oak</td>
<td>0.56</td>
<td>0.68</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(L_c/L_t)</td>
<td></td>
</tr>
</tbody>
</table>
3. 3. 4. Implications of apparent clumping index to vegetation clumping study
3. 3. 4. 1. Constraint on true clumping index

The $\Omega_{\text{app}}$ could be an upper limit of true $\Omega_E$ which is hard to quantify exactly. In Eq 3. 5, we assumed the numerator ($L_e$) may be estimated correctly by using LAI-2000. However, the denominator ($L$) needs special attention because individual measurements must meet the turbid media assumption (i.e. Poisson model of beam penetration through the canopy). Within one sample of the LAI-2000, light intensity at each ring is averaged over some azimuth range depending on the size of the view cap. However the Poisson assumption within each ring’s footprint is likely violated for heterogeneous canopies like a woody savanna site (Tonzi ranch) (Ryu et al. 2010). Thus, the denominator measured from the LAI-2000 is same or smaller than true $L$, consequently, $\Omega_{\text{app}}$ is the same or greater than $\Omega_E$. Therefore $\Omega_{\text{app}}$ is a useful quantity to check and constrain estimates of $\Omega_E$.

Our results suggest that the methodologies to quantify $\Omega_E$ might underestimate clumping effects because we did not find a significant difference between $\Omega_E$ and $\Omega_{\text{app}}$. For example, we compared $\Omega_{\text{app}}$ with TRAC-based $\Omega_E$ using a gap-size distribution analysis, the CC method (Chen and Cihlar 1995a; Leblanc 2002). The TRAC instrument measures sun-flecks over the forest floor and quantifies $\Omega_E$ using actual $P_a(\theta)$ and reduced $P_a(\theta)$ after removing large gaps that cannot happen in randomly distributed leaves (Leblanc 2002). The TRAC CC method has been widely used to quantify $\Omega_E$ but critical appraisal of this method has been rare (Macfarlane et al. 2007b; Ryu et al. 2010). We found that $\Omega_{\text{app}}$ and TRAC CC based $\Omega_E$ showed very good agreement ($y=0.98x$, $r^2=0.89$, $p<0.01$) and there was no significant difference between the two methods ($p>0.05$, paired t-test) (Figure 3. 4). Because TRAC and LAI-2000 use direct beam and diffuse radiation respectively, the direct comparison can lead to a mismatch of the spatial and angular footprints. Thus, the good agreement implies: 1) the limited spatial (dependent on limited transect length) and angular (dependent on solar position) footprint of the TRAC instrument may not account for some clumping effects, especially for heterogeneous ecosystem like savanna (Ryu et al. 2010) (instrument footprint issue) or 2) the large-gap removal process in the TRAC CC method may not perform correctly (algorithm performance issue). The first issue is an innate limitation of the TRAC instrument but the second issue could be improved using a new algorithm that combines the CC with the Lang and Xiang (1986) approach (Leblanc et al. 2005), which locally incorporates clumping effects using the CC method to make sure the denominator of Eq 3. 6 is close to true $L$. Actually, Leblanc et al (2005) reported that the mean $\Omega_E$ from 29 boreal forest sites was ~0.2 lower for the new algorithm than the CC method. Among the compiled LAI-2000 data base, few investigators reported the improved algorithm based $\Omega_E$; thus it was impossible to test the difference in $\Omega_E$ between CC and the improved algorithm across a diverse vegetation types. To quantify $\Omega_E$ correctly, further theoretical and experimental study is warranted and $\Omega_{\text{app}}$ will be a good quantity to constrain $\Omega_E$. Also the removal of between-crown gaps from total gaps to quantify LAI-2000-derived $\Omega_E$ is a subject for further study.
Element clumping index from TRAC, CC method

Figure 3. The scatterplot between apparent clumping index from LAI-2000 and element clumping index estimated from TRAC CC method (Chen and Cihlar 1995) that is corrected later by Leblanc (2002). The linear regression was forced to pass the origin.

3.3.4.2. Spatial scaling of clumping index

The spatial scaling of clumping effects has been unexplored in spite of its significance on large scale ecosystem modeling. From LAI-2000 datasets collected at landscape scale (See 2.4.), we tested how $\Omega_{\text{app}}$ changes with sample size (i.e. number of plots) (Figure 3. 5). First, we estimated $\Omega_{\text{app}}$ for each plot by applying Eq 3. 5. Then we averaged the values of $\Omega_{\text{app}}$ across the 20 plots, which resulted in 0.95. It is very close to the turbid media ($\Omega_{\text{app}} = 1$). Second, we estimated $\Omega_{\text{app}}$ differently by compiling all $P_d(\theta)$ data over 20 plots, then applying the Eq 3. 5. It produced 0.76. The two different calculation methods gave quite different $\Omega_{\text{app}}$ estimates. This highlights the non-linearity in clumping effects (logarithmic function in Eq 3. 5) at the landscape scale, and thus calculating the arithmetic average of $\Omega_{\text{E}}$ over multiple plots must be avoided. For example, let us assume that there are two plots; both plots have randomly distributed leaves in space but have different LAI (say, 1 vs 5). In this case, the arithmetic mean of $\Omega_{\text{app}}$ over the two plots will be 1. However, compiling all $P_d(\theta)$ data over the two plots and applying Eq 3. 5 should produce less than 1 because most importantly, the variance of $P_d(\theta)$ is no longer zero when combining two plots that have very different $L$. To determine $\Omega_{\text{app}}$ of a larger single plot that includes the two smaller plots, the latter approach must be used. In the ponderosa pine ecosystem, where
stands are mature, the $\Omega_{\text{app}}$ at the landscape scale can be obtained with only four plots within 5% difference from the landscape level $\Omega_{\text{app}}$, yet it is important to note that a landscape with relatively recent disturbances (harvest, fire) would require more plots. The magnitude of variation and shape of the curve will depend on the variation of canopy structures within ecosystems and the size of individual plots. Currently, the calculation methods of $\Omega_{\text{E}}$ are limited within one transect (TRAC) or one photo (digital hemispheric photography). To obtain $\Omega_{\text{E}}$ from multiple transects or photos, the non-linear process in spatial scaling of $\Omega_{\text{E}}$ must be incorporated, which would be relevant to validate a 7 km resolution global $\Omega$ map (Chen et al. 2005).

Figure 3.5. The relation between number of sampling plots and apparent clumping index derived from 20 plots (~120 LAI-2000 readings per plot) in Metolius, Oregon, USA (Law et al. 2001). The calculation of apparent clumping index at each sample size is explained in 3.2.4.

3.3.4.3. Seasonal variation of clumping index
The land surface modeling community has assumed that clumping is constant over seasons (Baldocchi et al. 2002; Houborg et al. 2009; Sampson et al. 2006) thus its temporal variation has been ignored. We found that $\Omega_{\text{app}}$ shows strong seasonality in phase with $L_c$ in a temperate deciduous forest (Harvard forest) (Figure 3.6a). During the dormant period, $\Omega_{\text{app}}$ (~0.83) was low mostly because of occasional evergreen trees (~10%, (Urbanski et al. 2007)), which caused the canopy to appear more clumped. With leaf out in deciduous species, $\Omega_{\text{app}}$ started to increase and it maintained peak values (~0.91) during summer. However, if a $\Omega_{\text{app}}$ value of 0.91 is used
for the dormant period of over story trees, then the direct beam penetrating the canopy will be underestimated by 16% which might be influential in interpreting the biogeochemistry of the understory, for example when calculating methane flux (Borken et al. 2006). On the other hand, an invasive plant infestation (Sherman Island) showed out-of-phase of $\Omega_{\text{app}}$ with $L_e$ (Figure 3. 6b). We assume that the observed pattern is related to the spatial heterogeneity of vegetation. During the growing season, the spatial distribution of pepperweed is heterogeneous and some portions of the landscape are bare soil, which creates a clumped canopy structure (lower $\Omega_{\text{app}}$). During the vegetation senescence, the pepperweed canopy transforms to a less clumped $\Omega_{\text{app}}$, a pattern opposite that of the deciduous forest. The difference between maximum and minimum $\Omega_{\text{app}}$ reached ~0.2 in the invasive infestation. Because the LAI-2000 has been routinely measured in various ecosystems, $\Omega_{\text{app}}$ could constrain the seasonal variation of $\Omega$, which may improve land surface models.
Figure 3. The seasonal variation of apparent clumping index with effective leaf area index measured from a temperate deciduous forest (Harvard forest) in 2006 and an invasive weed site (Sherman Island) in 2009.
3.4. Summary and Conclusions

In this study, we used a simple theoretical model, a forest gap fraction model, and LAI-2000 instrument raw data collected at 41 sites to investigate the correct estimation of $L_c$. Our main findings include:

1) The $\ln P_o(\theta)$ averaging method must be employed to obtain theoretically consistent $L_c$ from $P_o(\theta)$ measurements made with the LAI-2000 instrument.

2) When using $\ln P_o(\theta)$ as implemented in the LAI-2000 instrument and the accompanying software, clumping effects are partially considered and consequently estimates of $L_c$ more or less approximate $L$. A number of studies have quantified $L_c$ using the LAI-2000 instrument and accompanying software, and divided $L_c$ by $\Omega$ to obtain $L$ (Chen et al. 2006; Law et al. 2001a). This approach overcorrects for clumping effects and thus causes overestimation of $L$.

3) A forest gap fraction model showed that $\Omega_{app}$ was lowest for short tree heights, vertically prolonged crown shape and 80% canopy cover.

4) LAI-2000-derived $\Omega_{app}$ is a useful quantity that constrains true $\Omega_E$. Theoretically $\Omega_{app}$ is likely larger than $\Omega_E$ because of violation on the random distribution of leaves in space within each ring’s footprint in the LAI-2000 instrument. However, there was no significant difference between them in the four plant functional types. Thus current methods to calculate $\Omega_E$ might underestimate clumping effects.

5) $\Omega_{app}$ provides new insights into spatial and temporal variation of clumping effects. The individual $\Omega_E$ values at each plot must not be arithmetically averaged to obtain landscape level $\Omega_E$ due to the non-linear nature of the clumping index calculation. $\Omega_{app}$ showed seasonality in a deciduous forest site and an invasive plant infestation.

The method used to estimate $P_o$ correctly applies to digital hemispherical photography as well. First, $P_o(\theta)$ must be averaged over all photographs, then Miller’s theorem must be applied to quantify $L_c$. The results of our study have important implications for the evaluation of a satellite-based $L$ product or airborne laser scanning (LiDAR) based $L_c$. For example, the CYCLOPES $L$ product does not consider clumping effect at plant and canopy scale (Baret et al. 2007), thus to evaluate this product adequately, correct estimation of $L_c$ is crucial. Recently, LiDAR derived $L_c$ mapping has been proposed (Richardson et al. 2009; Solberg et al. 2009) but these studies used $\ln P_o(\theta)$ or the median of $P_o(\theta)$ instead of using $\ln P_o(\theta)$, which both incorporated clumping effects. We recommend the $\ln P_o(\theta)$ method be used to calculate $L_c$ in the protocols of canopy structure measurement (Law et al. 2008). Finally, the spatial and temporal variation of $\Omega_{app}$ would be useful to evaluate coarse resolution of a global $\Omega$ map and improve land surface models.
Chapter 4: Interannual variability of evapotranspiration and energy exchange over an annual grassland

4.1. Introduction

Evidence of global climate change is well-documented, with long-term increases observed in average global surface temperature (Houghton et al. 2001; Jones and Moberg 2003), the atmosphere’s carbon dioxide (CO2) concentration (Keeling et al. 1996), precipitation (Dai et al. 1997; Hulme et al. 1998), and runoff (Gedney et al. 2006; Groisman et al. 2004; Labat et al. 2004). However, there are still several unresolved critical issues relating to climate change. One issue is whether evapotranspiration (E) is increasing or decreasing. Even though there is general consensus that precipitation and runoff have increased (Dai et al. 1997; Gedney et al. 2006), the trend for E is still being debated. One may expect hydrological intensification and greater E with global warming (Huntington 2006), but there are many positive and negative feedbacks in play.

Some scientists argue that E has increased and has contributed to hydrological intensification (Brutsaert 2006; Golubev et al. 2001; Wetherald and Manabe 2002), while others argue that global dimming, caused by anthropogenic pollutants, has caused E to decrease and such dimming has dampened the water cycle (Liepert et al. 2004; Liu et al. 2004; Ramanathan et al. 2001; Roderick and Farquhar 2002a; Wild et al. 2004). This lack of consensus stems in part from a lacking of direct and long-term measurements of actual E. The majority of E measurements associated with this debate have been derived from pan E, which does not measure actual E (Morton 1978).

E is considered the most problematic term in the hydrological budget (Lettenmaier and Famiglietti 2006). It is generally evaluated as the residual between precipitation and runoff in the regional scale and as the residual between precipitation, runoff and interception at the catchment scale (Bosch and Hewlett 1982; Jaeger and Kessler 1997; Lewis et al. 2000; Marc and Robinson 2007). It is also estimated by measuring pan E (Brutsaert 2006; Brutsaert and Parlange 1998; Ohmura and Wild 2002; Peterson et al. 1995; Roderick and Farquhar 2002b). Indirect measures of E lack mechanistic information on biophysical processes, which include stomatal and

---

boundary layer conductances and leaf area index. Better and long-term information on $E$ from direct measurements is needed to better understand complex feedbacks between the terrestrial biosphere and climate system, for managing water resources, monitoring floods and droughts, and estimating the land surface energy balance that controls the height of the planetary boundary layer, climate and land-atmosphere feedback (Brubaker and Entekhabi 1996; Raupach 1998).

The eddy covariance method provides a direct means of measuring $E$ (Wilson and Baldocchi 2000). Due to its relatively short history, long-term studies using the eddy covariance technique are relatively rare compared to pan $E$. Five or more years of data on CO$_2$, water vapor, and energy exchange have been collected for the following ecosystems: boreal forests (Arain et al. 2002; Barr et al. 2007; Dunn et al. 2007), temperate deciduous forests (Barford et al. 2001; Carrara et al. 2003; Hanson et al. 2004; Wilson and Baldocchi 2001), savannas (Beringer et al. 2007; Ma et al. 2007), a steppe (Gilmanov et al. 2006), a subalpine forest (Monson et al. 2005), a shrub ecosystem (Luo et al. 2007), a northern peatland (Roulet et al. 2007), spruce forests (Grunwald and Bernhofer 2007; Hollinger et al. 2004), and a mixture of agricultural fields and forested patches (Haszpra et al. 2005). While all of the cited papers measure water vapor exchange, most focus on CO$_2$ exchange. To our knowledge, there are only a few publications covering more than five years for $E$ measurement explicitly, namely in a temperate deciduous forest (Hanson et al. 2004), a spruce forest (Grunwald and Bernhofer 2007), a bog (Lafleur et al. 2005), a chaparral (Luo et al. 2007), and boreal forests (Arain et al. 2002; Barr et al. 2007). Another cohort of studies have reported interannual variability of ET for less than five years in temperate deciduous forests (Moore et al. 1996; Wilson and Baldocchi 2000), boreal forests (Amiro et al. 2006; Arain et al. 2003), a cypress forest (Kosugi et al. 2007), a lake (Rouse et al. 2003), a tallgrass prairie (Burba and Verma 2005), a grassland (Jacobs et al. 2007a), an Amazonian rain forest (Hutyra et al. 2007), a maize-soybean agricultural system (Suyker and Verma 2007), and a savanna (Baldocchi et al. 2004). The eddy covariance method is susceptible to errors when the surface energy balance does not close and the flux tower is located on non-ideal terrain (e.g. rugged or heterogeneous landscapes) (Wilson et al. 2002). Its strengths, however, are in measuring interannual variability because bias errors tend to be constant from year to year.

Grasslands cover 20% of global land area (Wang et al. 2006a). They are of particular interest because it is not certain how water yield changes under land conversion from grassland to forest and vice versa (Marc and Robinson 2007), and their water vapor and CO$_2$ exchange is expected to respond to climate perturbations more sensitively (e.g. drought and extreme heavy rain event) (Knapp et al. 2002; Knapp and Smith 2001; Parton et al. 1994). Grassland $E$ studies have been performed in the Great Plains of North America (Bremer et al. 2001; Burba and Verma 2001; Burba and Verma 2005; Ham and Knapp 1998; Kim and Verma 1990; Meyers 2001; Verma et al. 2005).
1989, 1992), over a mixed grassland in Canada (Wever et al. 2002), a warm-temperate grassland in southeastern USA (Novick et al. 2004), a grass field (Saigusa et al. 1998) and a wet temperate grassland (Li et al. 2005) in Japan, a tussock grassland in New Zealand (Hunt et al. 2002), a C4 pasture in Brazil (Grace et al. 1998), and a perennial grassland in Netherlands (Jacobs et al. 2007a). The majority of these studies were conducted over relatively short periods, such as one year or less. Only two studies exist on \( E \) from the annual grasslands in a Mediterranean-type climate. One was for four months near the Pacific coast range of California (Valentini et al. 1995) and the other was for two years on the foothills of the Sierra Nevada mountains at the present study site (Baldocchi et al. 2004).

An annual grassland, growing in a Mediterranean-type climate in California, is unique from other grassland ecosystems because it has a different phenological cycles. The grasses live from November to May, during the winter rainy season and are dead during the summer months (Biswell 1956; Parton et al. 1994; Pitt and Heady 1978). Because the wet winter season receives the least solar radiation with the most rainfall, the water supply, precipitation, exceeds atmospheric demand for water, potential \( E (E_p) \). However, during the dry season, grasslands receive the highest solar radiation with least rainfall, causing the potential water demand to greatly exceed water supply. Budyko’s aridity index (AI) is given as the ratio of precipitation to \( E_p \) and is widely used to determine whether a region is water-limited (AI<1) or energy-limited (AI>1) (Baldocchi and Xu 2007; Budyko 1974; Donohue et al. 2007; Farquhar and Roderick 2007; Yang et al. 2006). This ecosystem is relatively unique because it undergoes both pronounced water-limited and energy-limited periods in the same year. Consequently, the study of intra-annual variability of \( E \) can help understand which period influences annual \( E \) most and how the timing of transition from energy-limited to water-limited modulates the annual \( E \) amount. Furthermore, because this ecosystem experiences large interannual variability in precipitation (376 mm to 888 mm per year during the study period), it is critical to understand how \( E \) is down-regulated with soil water deficits.

Here, we report on six hydrological years of \( E \) and energy exchanges over an annual grassland growing in the Mediterranean-type climate of California. Direct measurements of \( E \) were made with the eddy covariance method between July 2001 to June 2007. The objectives of this study include: 1) to characterize \( E \), energy fluxes and related bulk parameters (e.g. surface conductance, decoupling factor and Priestley-Taylor \( \alpha \) coefficient) in monthly and annual time scales, and 2) to investigate which abiotic and biotic factors control the interannual variability of water and energy fluxes. Additionally, we will use our data to address questions related to \( E \) biogeography for classifying plant functional type (PFT). The scientific questions to be addressed in this study include: 1) how will growing season length influence annual \( E \) amount?; 2) How does the timing of transition from energy-limited to water-limited modulate annual ET amount?; 3) Which
factors control $E$-atmospheric demand or stomatal regulation?; and 4) How does $E$ respond to changes in solar radiation amounts in water-limited and energy-limited periods?

4. 2. Materials and Methods

4. 2.1. Site description

The study site is a member of the AmeriFlux network and is classified as a grazed annual grassland in central California, USA (Vaira Ranch, latitude: 38.4133°N; longitude: 120.9508°W; altitude: 129 m). It is located on the lower foothills of the Sierra Nevada Mountains. It experiences a Mediterranean-type climate with dry hot summers and wet mild winters. Rainfall is concentrated between November and May with little precipitation during the summer. Climate data show that the annual average temperature and annual precipitation amount are 16.9°C and 565 mm, respectively (1949 to 2005 data from the Camp Pardee, CA climate station, which is at a similar altitude and is 26 km south of the study site: http://www.wrcc.dri.edu/cgi-bin/cliMAIN.pl?cacamp+nca). The soil is an Exchequer very rocky silt loam (Lithic xerorthents), which is composed of 30% sand, 57% silt and 13% clay. The bulk density at the surface layer (0-30 cm) is 1.43±0.10 g cm$^{-2}$. The soil profile is about 0.5 m depth with overlying fractured rock. The site is dominated by the cool-season C$_3$ annual species, including *Brachypodium distachyon* L., *Hypochaeris glabra* L., *Trifolium dubium* Sibth., *Trifolium hirtum* All., *Dichelostemma volubile* A., and *Erodium botrys* Cav. More detailed site information may be found in previous studies (Baldocchi et al. 2004; Xu and Baldocchi 2004).

4. 2.2. Data acquisition

Water vapor, CO$_2$, energy fluxes and meteorological variables have been measured since November 2000. The eddy covariance system is comprised of a triaxial sonic anemometer (Model 1352, Gill Instruments Ltd., Lymington, England) and an open-path fast response infrared gas analyzer (IRGA, Li 7500, Li-Cor Inc., Lincoln, NE, USA). The sensors were mounted at 2 m height above the ground. The fetch from all direction was over 200 m and only a few sparse oak trees were within the footprint area (Kim et al. 2006). Radiation flux densities were measured at 2.5 m height with an upward and downward facing quantum sensor (PAR Like, Kipp and Zonen, Delft, Netherlands), a net radiometer (NR Lite, Kipp and Zonen, Delft, Netherlands) and a pyranometer (CM11, Kipp and Zonen, Delft, Netherlands). Air temperature and relative humidity were measured at 2.5 m height with a shielded and aspirated sensor (HMP-35 A, Vaisala, Helsinki, Finland). Soil volumetric water content was measured at the depths of 0.05, 0.1, and 0.2 m with frequency domain reflectometry sensor (ML2-X, Delta-T Devices, Cambridge, UK). Green leaf area index ($L_G$) was determined by harvesting four sample plots (0.25 m × 0.25 m) within the footprint of flux tower when the grass was living. The dates of
grass germination and senescence were detected based on the extrapolation of data obtained during periodic field visits (weekly to bi-weekly). The growing season length was calculated from these values (Ma et al. 2007). Additional details on the data acquisition are available in previous papers (Baldocchi et al. 2004; Xu and Baldocchi 2004).

4.2.3. Gap filling, assessing uncertainty, and data processing

Data gaps are unavoidable in long-term and continuous measurements. We filled short data gaps (<3 hours) with linear interpolation and we used the mean diurnal method for filling longer gaps (Falge et al. 2001). The diurnal means were calculated for 26 consecutive day windows, which correspond well with a spectral gap in energy fluxes in the site (Baldocchi et al. 2004). For periods with missing solar radiation, air temperature and precipitation data, we used the measurements from the nearby companion site (Tonzi Ranch, 2 km away). We compared numerous meteorological variables between the two sites and found that they were interchangeable. For assessing the data quality, we analyzed the linear regressions of the sum of latent heat ($\lambda E$), sensible heat ($H$) and soil heat flux densities ($G$) against the net radiation ($R_n$). The half hourly data, which excluded gap filled data, were used to perform the linear regression analysis. The annual sum of $\lambda E + H + G$ divided by annual sum of $R_n$ is presented in Table 4.1. In general, energy balance closure on annual time scales ranged between 0.92 and 1.12 with an average of 1.00. Although not perfect, our ability to close the surface energy was better than the average energy closure across FLUXNET sites for shorter term periods (0.80) (Wilson et al. 2002) and was comparable to the comprehensive studies over short vegetation (Heusinkveld et al. 2004; Meyers and Hollinger 2004).

Table 4.1. Annual energy balance closure for linear regression coefficients and the ratio of $\lambda E + H + G$ to $R_n$.

<table>
<thead>
<tr>
<th>year*</th>
<th>slope</th>
<th>intercept (W m$^{-2}$)</th>
<th>$r^2$</th>
<th>($\lambda E + H + G$)/$R_n$</th>
</tr>
</thead>
<tbody>
<tr>
<td>01_02</td>
<td>0.90</td>
<td>2.11</td>
<td>0.97</td>
<td>0.92</td>
</tr>
<tr>
<td>02_03</td>
<td>0.90</td>
<td>4.03</td>
<td>0.98</td>
<td>0.95</td>
</tr>
<tr>
<td>03_04</td>
<td>0.86</td>
<td>7.10</td>
<td>0.97</td>
<td>0.94</td>
</tr>
<tr>
<td>04_05</td>
<td>0.81</td>
<td>15.25</td>
<td>0.97</td>
<td>1.02</td>
</tr>
<tr>
<td>05_06</td>
<td>0.88</td>
<td>18.84</td>
<td>0.97</td>
<td>1.12</td>
</tr>
<tr>
<td>06_07</td>
<td>0.87</td>
<td>14.21</td>
<td>0.97</td>
<td>1.04</td>
</tr>
</tbody>
</table>

*Year was defined as hydrological year (e.g., July to June). 01_02 indicates July 2001 to June 2002.

$\lambda E$: latent heat flux

$H$: sensible heat flux
For quantifying uncertainties associated with the annual sum of \( E \), we used the bootstrap technique with the Monte Carlo approach (Efron and Tibshirani 1993). It estimates bias, standard error, confidence interval or prediction intervals. In prior studies, it has been used to assess uncertainties of gross primary production (Hagen et al. 2006; Ma et al. 2007). We assessed the uncertainty of each annual \( E \) sum at the 90\% confidence interval. The confidence intervals for annual \( E \) are shown in Table 4. 2.

In order to distill and interpret the large amount of information collected over six years, we relied on and presented monthly-averages of daily sums of solar radiation (\( R_s \), \( R_n \), \( \lambda E \), \( H \) and \( G \)). Baldocchi et al. (2001b) reported that there is a pronounced spectral gap in \( E \) and CO₂ exchange at the monthly scale, making it an appropriate time-step to capture seasonal and phenological change. This time-step is also used in other interannual studies on \( E \) (Arain et al. 2002; Lafleur et al. 2005). In analyzing annual sums of \( E \) and meteorology, we used the hydrological year, defined as the period from July of current year to June of next year (e.g. 03_04 is from July 2003 to June 2004). This is standard practice for hydrological analyzes in California because it was necessary to include the entire rainy season (November to May) into one year.

### 4. 2.4. Calculations of bulk parameters

To interpret the interannual variability of \( E \) and energy fluxes, we used three model parameters: bulk surface conductance (Monteith 1965), decoupling factor (Jarvis and McNaughton 1986), and the Priestley-Taylor \( \alpha \) coefficient (Priestley and Taylor 1972).

The bulk surface conductance \( (G_s) \) is related to the weighted integration of individual leaf’s conductance (Baldocchi and Meyers 1998; Raupach 1995) and it was computed by inverting from the Penman-Monteith equation:

\[
\frac{1}{G_s} = \frac{1}{G_a} \left\{ \frac{\varepsilon(R_a - G) + \rho C_p G_a D / \gamma}{\lambda E} - \varepsilon \right\} - 1
\]

(4. 1)

where \( \rho \) is air density (kg m⁻³), \( C_p \) is specific heat capacity of air (J kg⁻¹ K⁻¹), \( \varepsilon \) is \( s/\gamma \), \( s \) is the slope of relation between saturation vapor pressure and temperature, \( \gamma \) is psychrometric constant,
$D$ is vapor pressure deficit (kPa) and $G_a$ is bulk aerodynamic conductance. $G_a$ was calculated as follows:

$$R_a = R_{a,m} + R_b \quad (4.2)$$

$$R_{a,m} = \frac{u}{u^*}^2 \quad (4.3)$$

$$R_b = kB^{-1} / ku_\ast \quad (4.4)$$

where $R_a$ (bulk aerodynamic resistance) is a reciprocal of $G_a$, $R_{a,m}$ is aerodynamic resistance for momentum transfer, $R_b$ is quasi-laminar boundary layer resistance (Thom 1972), $k$ is von Karman constant (0.4), $u^*$ is friction velocity, which was measured directly with the eddy covariance system. The structure of the land surface determines $kB^{-1}$. In this case, a value of 2 was used because it is a representative value for the dense grass canopies (Garratt and Hicks 1973; Verma 1989).

The decoupling factor ($\Omega$) explains the degree of coupling between vegetation and atmosphere. It ranges from 0 when $E$ is controlled by $G_s$ and vapor pressure deficit to 1 when $E$ is controlled by the available energy (Jarvis and McNaughton 1986). It was calculated as follows:

$$\Omega = \frac{\varepsilon + 1}{\varepsilon + 1 + \frac{G_a}{G_s}} \quad (4.5)$$

The Priestley-Taylor $\alpha$ coefficient represents the ratio between measured $\lambda E$ and equilibrium evaporation ($\lambda E_{eq}$)

$$\alpha = \frac{\lambda E}{\lambda E_{eq}} \quad (4.6)$$

where $\lambda E_{eq}$ is equilibrium $\lambda E : s + \gamma$. It provides a comparison of measured $\lambda E$ to a climatologically expected $\lambda E$ assuming a closed volume with constant net radiation over a wet surface (McNaughton and Spriggs 1986). Potential $\lambda E$ was calculated from $1.26 \times \lambda E_{eq}$ (Priestley and Taylor 1972).
To avoid the numerical instability that occurs when the denominator approaches zero, only daytime data of $G_s$, $\Omega$ and $\alpha$ (10:00 to 14:00) were used to calculate the monthly mean values.

4.3. Results

4.3.1. General weather conditions and phenology

The average annual air temperature during the 6-year period was 15.8°C with the minimum of 15.3°C in the 04_05 hydrological year and maximum of 16.3 °C in the 03_04 hydrological year (Table 4.2). The monthly average of the daily maximum air temperature ($T_x$) ranged from 10°C to 20°C in the wet seasons and reached extreme levels (~35°C) in the dry seasons (Figure 4.1a). The monthly average of the daily minimum air temperature ($T_n$) remained positive, indicating that the site did not experience prolonged periods of freezing (Figure 4.1a). The ecosystem experienced a wide diurnal temperature difference (i.e. $T_x$ minus $T_n$), which ranged from 20°C during the dry seasons when the grass was dead to 10°C in the wet seasons when the grass actively transpired. The annual precipitation showed large interannual variation. It ranged between 376 mm (06_07 hydrological year) and 888 mm (05_06 hydrological year), producing an average and standard deviation of 561 mm and 198 mm, respectively (Figure 4.1b). The monthly precipitation showed that the 04_05 hydrological year experienced the longest wet season ranging from October to June, whereas the 03_04 hydrological year underwent the shortest wet season from November to March (Figure 4.1b). Due to the Mediterranean-type climate, over 90% of annual precipitation fell during the November to April wet season. The soil profile experienced extremely dry conditions during the summer, and soil moisture was recharged by the winter rainfall (Figure 4.1b). $L_G$ showed that winter rainfall triggered slow vegetation growth, which accelerated in spring due to the availability of ample soil moisture and which reached maximum values in April or May (Figure 4.1c). The maximum growth period did not last very long, and the grass quickly senesced in response to the subsequent soil moisture deficits and high air temperatures.

Table 4.2. Summary of energy fluxes, climatology, and bulk parameters for the 6-year.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Year</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>01_02</td>
</tr>
<tr>
<td>Solar radiation (GJ m$^{-2}$)</td>
<td>6.69</td>
</tr>
<tr>
<td>Net radiation (GJ m$^{-2}$)</td>
<td>2.18</td>
</tr>
<tr>
<td>Latent heat flux (GJ m$^{-2}$)</td>
<td>0.72</td>
</tr>
<tr>
<td>Sensible heat flux (GJ m$^{-2}$)</td>
<td>1.34</td>
</tr>
<tr>
<td>Soil heat flux (GJ m⁻²)</td>
<td>0.00</td>
</tr>
<tr>
<td>------------------------</td>
<td>------</td>
</tr>
<tr>
<td>% flux data coverage</td>
<td>59</td>
</tr>
<tr>
<td>Temperature (°C)</td>
<td>15.5</td>
</tr>
<tr>
<td>Vapor pressure deficit (kPa)</td>
<td>0.99</td>
</tr>
<tr>
<td>Precipitation (mm)</td>
<td>500</td>
</tr>
<tr>
<td>Evapotranspiration (mm)</td>
<td>292 (±25)</td>
</tr>
<tr>
<td>Potential evaporation (mm)</td>
<td>879</td>
</tr>
<tr>
<td>α (year)</td>
<td>0.47</td>
</tr>
<tr>
<td>α (growing season)</td>
<td>0.89</td>
</tr>
<tr>
<td>Gₛ (mm sec⁻¹) (year)</td>
<td>4.01</td>
</tr>
<tr>
<td>Gₛ (mm sec⁻¹) (growing season)</td>
<td>9.01</td>
</tr>
<tr>
<td>Ω (year)</td>
<td>0.27</td>
</tr>
<tr>
<td>Ω (growing season)</td>
<td>0.55</td>
</tr>
<tr>
<td>Growing season length (days)</td>
<td>154</td>
</tr>
<tr>
<td>Max LAI</td>
<td>2.6</td>
</tr>
</tbody>
</table>

*The parenthesis indicates 90% of confidence interval estimated from bootstrap technique

* Priestley-Taylor α coefficient

* Growing season indicates from January to April

* Bulk surface conductance

* Decoupling factor
Figure 4.1. (a) Monthly average of daily maximum ($T_d$) and minimum ($T_n$) air temperature. (b) Monthly average of volumetric soil water content at 5-cm depth ($\theta_v$), and monthly sum of precipitation (Ppt). (c) Green leaf area index ($L_G$). $L_G$ was measured periodically so it is marked in daily scale on the graph. (d) Monthly average of daily-integrated net radiation ($R_n$), latent heat flux ($\lambda E$), sensible heat flux ($H$), and soil heat flux ($G$). (e) Monthly average of bulk surface conductance ($G_s$).

4.3.2. PAR albedo

The monthly trends in the albedo of photosynthetically active radiation (PAR albedo) are shown in Figure 4.2a. The PAR albedo is related to plant greenness rather than energy availability.
because reflected near infrared radiation is missing. The canopy growth is related to the radiation absorption, particularly PAR (Burba and Verma 2001; Monteith and Unsworth 1990; Song 1999). The monthly PAR albedos showed a clear seasonal pattern with the annual average ranging between 0.102 and 0.124. In general, PAR albedo decreased abruptly in November and December due to the start of rainfall and greenness. It reached its minimum values (between 0.05 and 0.08) in April. Afterward, PAR albedo quickly increased with the start of senescence. The PAR albedo showed the earliest onset of growing season (i.e. the lowest PAR albedo in November and December) and the latest senescence (i.e. the lowest PAR albedo in June) in the 04_05 hydrological year. This observation is consistent with the fact that that year had the longest growing season. The PAR albedo scaled negatively with \( L_G \), implying that PAR albedo can capture phenological events and canopy structure (Figure 4.2b) well. In August of the 03_04 hydrological year, the PAR albedo decreased abruptly in contrast to the other years because of an uncommon summer rainfall event (Figure 4.1).
Figure 4.2. (a) Monthly average of daily PAR albedo for the 6-year period. Monthly average was calculated from the ratio of the sum of outgoing PAR to the sum of incoming PAR for each month. 01_02 indicates July 2001 to June 2002. (b) The relationships between green leaf area index ($L_G$) and PAR albedo during the growing seasons. PAR albedos are daily average values from 10:00 to 14:00.

4.3.3. Radiation and energy flux densities

The average annual integral of shortwave radiation, $R_g$, during the 6-year period was 6.62 GJ m$^{-2}$. During the dry season, $R_g$ showed the similar pattern, year to year, because the skies tend to be...
cloudless. High interannual variations are attributed to levels of cloudiness during in the wet seasons, which affects rainfall, too (Figure 4. 3a).

Figure 4. 3. (a) Monthly average of daily integrated solar radiation for 6-year. (b) Monthly average of daily integrated latent heat flux for 6-year period. 01_02 indicates July 2001 to June 2002.

The averaged annually integrated net radiation balance, $R_n$, over 6-year was 2.21 GJ m$^{-2}$. This value is about 33% of annual $R_g$ (6.62 GJ m$^{-2}$). Net radiation is relatively low because the annual
grassland has bright reflective dead vegetation in summer. In addition, the surface is very hot in summer when the grass is dead and does not transpire. Therefore, the outgoing longwave radiation is substantially greater than incoming longwave radiation, causing a net loss of longwave energy (Figure 4. 4). On an annual time scale, the main consumer of $R_n$ in the annual grassland was sensible heat exchange, $H$, (67% of $R_n$). In comparison, $\lambda E$ is smaller because it only occurs in the wet seasons when the $R_n$ is small (Figure 4. 1). On a monthly time scale, 85% of $R_n$ was used by $\lambda E$ in the growing season (January to April), whereas only 5% in the dry season (July to September). Annual sums of $\lambda E$ ranged from 0.66 to 0.99 GJ m$^{-2}$ and showed a repeatable seasonal pattern from July to March during the 6-year under investigation. On the other hand, $\lambda E$ experienced high interannual variability between May and June, which in turn controlled the interannual variability in annual sums of $\lambda E$ (Figure 4. 3b). On an annual basis, the ratio of $E$ to precipitation ranged from 0.39 (05_06 hydrological year) to 0.80 (06_07 hydrological year) with an average of 0.53. It is notable that the 06_07 hydrological year with the lowest rainfall (376 mm) evaporated 303 mm of water, whereas the 05_06 hydrological year had the highest rainfall (888 mm) with just 343 mm of evaporation. These data imply that the majority of rainfall either ran off or infiltrated into the unsaturated zone of the subsurface and recharged the groundwater. A large transition in $\lambda E$ and $H$ occurred during the senescence periods, which is in agreement with observations over a tallgrass prairie (Ham and Knapp 1998) (Figure 4. 3b). On an annual scale, $G$ was negligible and nearly zero during the 6-year period.
4.3.4. Bulk parameters

On an annual time scale, average surface conductance, $G_s$, ranged between 2.8 mm sec$^{-1}$ (03_04 hydrological year) and 5.8 mm sec$^{-1}$ (04_05 hydrological year) (Table 4. 2). Monthly $G_s$ in that year showed the lowest maximum $G_s$ value (around 7 mm sec$^{-1}$) during the 6-year and approached zero in May (Figure 4. 1e). In contrast, the hydrological year, 04_05, showed higher maximum $G_s$ value (around 13 mm sec$^{-1}$) and maintained 3 mm sec$^{-1}$ by June (Figure 4. 1e). Among the 6-year data record, only the hydrological year, 04_05, received rainfall (22 mm) in June and this rainfall extended growing season length, causing higher $G_s$ in June than the other years. Overall, $G_s$ decreased exponentially with $D$ (Figure 4. 5). In the dry season (July and September), $D$ ranged from 2.3 to 4.1 kPa and $G_s$ was nearly zero, whereas in wet season (December to April), $D$ was less than 1.5 kPa and $G_s$ ranged from 4 to 15 mm sec$^{-1}$. $G_s$ in two transitional periods (i.e. October to November and May to June) responded differently to similar $D$ values (~1.5 kPa). In October to November, the grass started to germinate so that $L_G$ is very low, less than 0.5 (Figure 4. 1c), causing low values of $G_s$ (~1 mm sec$^{-1}$) too. In contrast, $G_s$ in May and June reached 8 mm sec$^{-1}$ because several years maintained the high $L_G$ with ample soil moisture in this period (e.g. 04_05 year). Consequently, $G_s$ was more sensitive to $D$ in May and June. The average coupling coefficient, $\Omega$, during the 6-year period was 0.27, indicating that $E$ is tightly controlled by its surface conductance (Table 4. 2). On an annual time scale, the average $\alpha$ was 0.45, roughly half of $\lambda E_{eq}$. On a monthly scale, the maximum $\alpha$ reached 0.97 in March of the 05_06 and 06_07 hydrological years (not shown in this paper). It indicates that maximum $\lambda E$ was comparable to the equilibrium $\lambda E$ over a wet vegetated surface.
Figure 4.5. The relationships between monthly average vapor pressure deficit ($D$) and $G_s$ during the 6-year period. Monthly $G_s$ and $D$ were averaged from daytime values (10:00 to 14:00).

4.4. Discussion

4.4.1. Comparison of energy fluxes with other studies

The average annual $R_g$ during the 6-year period was 6.62 GJ m$^{-2}$. This is higher than the tallgrass site (5.8 GJ m$^{-2}$) whose latitude is lower than this study site by two degrees (Burba and Verma 2005) and it is among the highest values observed in North and South America (Ohmura and Gilgen 1993). The high annual energy flux of $R_g$ is due to the clear skies in the summer. The averaged annually integrated $R_n$ balance during the 6-year period was 2.21 GJ m$^{-2}$. The annual $R_n$ is lower than the reports of 3.03 GJ m$^{-2}$ (Wilson and Baldocchi 2000) and 2.55 GJ m$^{-2}$ (Oliphant et al. 2004) over temperate deciduous forests, 2.68 GJ m$^{-2}$ over a cypress forest in Japan (Kosugi et al. 2007), 3.15 GJ m$^{-2}$ over a woody savanna ecosystem in western US (Baldocchi et al. 2004), 2.82 GJ m$^{-2}$ over a temperate pine plantation forest in Canada (Restrepo and Arain 2005), 4.09 GJ m$^{-2}$ (Malhi et al. 2002), 3.89 GJ m$^{-2}$ (da Rocha et al. 2004) and 3.82 GJ
m$^{-2}$ (Vourlitis et al. 2002) over Amazonian rain forests in Brazil, 3.02 GJ m$^{-2}$ (Burba and Verma 2005) and 2.56 GJ m$^{-2}$ (Li et al. 2005) over grasslands. Only a woody savanna site after harvest in France (Kowalski et al. 2003) and a Douglas fir forest in Canada (Humphreys et al. 2003) experienced lower $R_n$ values than this study, e.g. 1.96 GJ m$^{-2}$ and 2.13 GJ m$^{-2}$, respectively. It is notable that all the cited sites received less $R_g$ than the study site, indicating that the annual grassland site received the highest energy but was least efficient in converting it to the available energy for work.

Average annual $E$ (319 mm) was comparable to many other studies in other climates and over different plant functional types. It is comparable to 320 mm (Kljun et al. 2006) and 321 mm (Lee et al. 1999) over Boreal mixed forests in Canada, 303 mm (Kljun et al. 2006) and 320 mm (Owen et al. 2007) over Boreal evergreen needleleaf forests in Canada and Finland, and 321 mm over a mixed forest in Italy (Owen et al. 2007). A few sites reported less annual $E$ than this study site, namely 126 mm over a broadleaf deciduous forest in Finland (Aurela et al. 2001), 146 mm over a deciduous needleleaf forest in Russia (Dolman et al. 2004), 180 mm over an open shrubland in Israel (Grunzweig et al. 2003), 220 mm over a deciduous broadleaf forest in Denmark (Owen et al. 2007), and 255 mm (Wever et al. 2002), 225 mm (Amiro et al. 2006), 237 mm (Kljun et al. 2006) over a Boreal grassland, a mixed forest, and a evergreen deciduous forest in Canada.

4.4.2 Constraints on E

4.4.2.1 Water and energy

From the standpoint of climatology, the annual grasslands of Mediterranean-type climate zones are classified as a semi-arid region, indicating that they are water-limited (Biswell 1956). On an annual time scale, the Budyko’s AI (i.e. precipitation/$E_p$) of the study site ranged from 0.39 (03_04 year) to 0.91 (05_06 year) with the average equaling 0.59 (Table 4.2), confirming that this ecosystem is water-limited. Examining data on the monthly time scale, however, indicates that each year experienced both pronounced water-limited (dry season) and energy-limited (wet season) periods (Figure 4.6). During the dry season, $E_p$ (i.e. water demand) was much higher than precipitation (i.e. water supply), causing AI to approach zero. Therefore, actual $E$ ($E_a$) in the dry season is restrained by precipitation (i.e. water-limited). During August 2003, there was an uncommon summer rainfall event, and all rainfall evaporated (Figure 4.6). In contrast, during the wet season, precipitation is higher than $E_p$, forcing AI to exceed 1 (i.e. energy-limited). Regardless of the precipitation amount, $E_a$ was tightly controlled by $E_p$ in the wet season. For example, there was heavy rainfall reaching 300 mm in December 2005; however, $E_a$ was only 18 mm because $E_p$ was just 19 mm and $E_a$ was confined by $E_p$. Theoretically, $E_a$ should be less than the minimum of $E_p$ and precipitation (Farquhar and Roderick 2007). However, we found that $E_a$
was higher than precipitation but lower than $E_p$ in April or May (e.g. 2005 May). It was reported that the soil water holding capacity of the root zone is about 132 mm at this study site (Baldocchi et al. 2004). Therefore, some portion of precipitation in the previous month can be stored in the soil and used in the next month, causing $E_a$ to be higher than precipitation. Also, it should be noted that the majority of heavy precipitation (e.g. 300 mm in 2005 December) will runoff or infiltrate into ground water considering the nearly saturated state of the subsurface and shallow rooting depth (Aanderud et al. 2003; Joffre and Rambal 1993). Because Budyko’s framework assumes that soil water storage and the macro-climate are at steady-state and does not consider the role of vegetation, one should be cautious about interpreting Budyko’s AI on short spatial and temporal scales (Donohue et al. 2007).

Figure 4.6. Time series of monthly sum of actual $E$ ($E_a$), potential $E$ ($E_p$) and precipitation (Ppt) from July 2001 to June 2007. Vertically dashed lines indicate January for each calendar year.

The relationship between monthly $R_g$ and $\lambda E$ helps us interpret how $E$ is modulated by the energy- and water-limited periods (Figure 4. 7a). From July to September, $\lambda E$ was nearly zero and was not influenced by $R_g$ amount because this is the dry season and there is nearly no water in the soil. In October and November, $\lambda E$ was negatively correlated to $R_g$. Precipitation in this period is critical to grass germination and growth (Pitt and Heady 1978). So $E$ favors less $R_g$, more clouds and more frequent wet surface conditions. In December to April, $\lambda E$ scaled positively with $R_g$ amount because there is ample water supply but paucity of available energy (i.e. energy-limited period). In May to June, $\lambda E$ showed remarkably negative correlation to $R_g$. In this water-limited period, $R_g$ was negatively correlated to soil water content. Therefore, less $R_g$ with higher soil water content could increase $\lambda E$ under higher water demand (Figure 4. 7b). A companion study also reported that precipitation in this period was critical for extending the growing season length and increasing carbon uptake (Ma et al. 2007).
Figure 4. 7. (a) The relationships between monthly average daily solar radiation and monthly average daily latent heat flux during the 6-year period. Dashed lines indicate 95% confidence interval of the linear regressions. (b) The relationship among monthly average daily solar radiation, monthly average volumetric soil water content at 5-cm depth ($\theta_v$), and monthly average daily latent heat flux in May and June during the 6-year period. The points indicate the green upside-down triangles in (a).
4.4.2.2. Physiological control via surface conductance

Maximum daily $G_s$ values reached 25 mm sec$^{-1}$ (not shown in the graph), which is comparable values reported for tallgrass prairie of the Great Plains; 25 mm sec$^{-1}$ (Kim and Verma 1990) and 20 mm sec$^{-1}$ (Stewart and Verma 1992). It is lower than the canopy conductances for cultivated crops of the Great Plains; 29 mm sec$^{-1}$ for maize and 38 mm sec$^{-1}$ for soybean (Suyker and Verma 2007). The maximum $G_s$ value at our study site is one of the highest values reported across diverse ecosystems (Kelliher et al. 1995). This was possible due to ample water in the growing season and high leaf nitrogen values ranging between 2 and 4% (not published), comparable to cultivated crops ranging between 1 and 5% (Suyker and Verma 2007).

On an annual time scale, average $\alpha$ was 0.45. This is lower than the report of 0.8 for a Douglas fir forest in Canada (Humphreys et al. 2003) and the report of 0.72 for a temperate deciduous forest in south-eastern US (Wilson and Baldocchi 2000). It has been reported that the relation between $G_s$ and $\alpha$ can represent the interactive effects of $L_G$, soil water status and photosynthetic capacity of any PFTs (Baldocchi et al. 1997; Baldocchi and Xu 2007; deBruin 1983; McNaughton and Spriggs 1989). In our 6-year study, the monthly $G_s$ scaled with $\alpha$ regardless of interannual and seasonal variation of precipitation and $E$, supporting previous studies (Figure 4. 8). On the monthly scale, $\alpha$ did not exceed one, indicating $E_{eq}$ approximately establishes the upper limit of $E_a$ of annual grassland. Under dry canopies with well-watered soil and high available energy, $\alpha$ of crops approaches 1.26 (i.e. $E_p$) (deBruin 1983; McNaughton and Spriggs 1989; Priestley and Taylor 1972). It is notable that the annual grassland grows in winter when $R_g$ is the least, so it does not readily reach the $E_p$ even though it has ample soil water. A theoretical study showed that $\alpha$ is insensitive to $G_s$ when $G_s$ exceeds about 16 mm sec$^{-1}$ (McNaughton and Spriggs 1986). Our result showed that two variables have logarithmic relation and that $\alpha$ is insensitive to $G_s$ over 12 mm sec$^{-1}$, supporting the theoretical study.
Figure 4. 8. The relationships between monthly average bulk surface conductance ($G_s$) and Priestly-Taylor $\alpha$ coefficient. Monthly $G_s$ and $\alpha$ were averaged from daytime values (10:00 to 14:00).

4. 4. 2. 3. Main determinant on annual ET amount: Growing season length

Many studies have reported that longer growing seasons enhance annual carbon uptake (Baldocchi et al. 2001a; Churkina et al. 2005). However, there are few studies that have investigated the effect of growing season length on annual $E$. In annual grassland, we observed a tight correlation between the hydrological growing season length and annual $E$ amount (Figure 4. 9). This ecosystem showed the distinct transition of $\lambda E$ in senescent period rather than the onset of a greenness period, contrary to observations in deciduous forests (Moore et al. 1996; Wilson and Baldocchi 2000) (Figure 4. 3b). Therefore, the timing of the onset of the senescence period is more critical to the annual $E$ amount than the earlier onset of greenness period. It was reported that an earlier spring uses the soil water reservoir sooner and leads to summer drought in Northern Hemisphere (Angert et al. 2005). An analysis on NDVI, precipitation and surface temperature data in North American grasslands reported that lengthening growing season does
not necessarily lead to more $E$ (Wang et al. 2006b). These arguments are not applicable to the annual grassland because it has a different phenological pattern (i.e. dead in summer and active in winter). Therefore, annual $E$ scaled with the hydrological growing season length rather than the frost free growing season. These results are consistent with reports in our companion paper that annual gross primary productivity scaled with the length of the growing season at the site (Ma et al. 2007).

**Figure 4. 9.** The relationships between growing season lengths and annual $E$ during the 6-year period. $b[0]$ and $b[1]$ indicate intercept and slope, respectively. Dashed lines indicate 95% confidence interval for linear regression lines.

### 4. 4. 3. Application of long-term flux measurements to testing a plant functional type scheme

Understanding the biophysical behavior of plant function is important for upscaling flux measurements to regional and continental level. Also, the mechanistic determination of PFTs is of particular importance for predicting the distribution of vegetation under climate change because PFTs are central to global dynamic vegetation models (Cramer et al. 2001). The PFTs
are categorized using climate and vegetation information (Bonan et al. 2002; Holdridge 1947; Stephenson 1990; Woodward and Lomas 2004). One widely used scheme for PFTs classification is the water balance approach. Traditionally, $E_a$ was estimated as a function of air temperature (Thornthwaite 1948) or as the residual between precipitation and runoff (Eagleman 1976). The long-term measurement of $E_a$ from flux towers provides an excellent opportunity to revise and refine the water balance driven PFTs classification. Stephenson (1990) proposed a vegetation distribution map based on the relation between annual $E_a$ and water deficit (i.e. $E_p$-precipitation) over North America. However, it evaluated $E_a$ indirectly using the water balance method (Eagleman 1976). We compiled $E_a$ and water deficit data across several ecosystems from the published data (Figure 4.10). Overall, annual $E_a$ scaled negatively with annual water deficit, implying that biological stress (i.e. water deficit) may control annual $E_a$. Our 6-year direct $E_a$ measurement over the annual grassland showed that the water deficit and $E_a$ ranged from 100 to 650 mm and from 270 to 390 mm, respectively. We found that the ranges belong to the grassland of California in Stephenson’s PFT scheme. However, annual $E_a$ of a temperate deciduous forest in south-western US (Wilson and Baldocchi 2000) ranged from 537 to 611 mm, which is slightly lower than Stephenson’s guideline of $E_a$ (600 to 1400 mm) for this ecosystem. Also, Stephenson’s classification only covered positive water deficit, but the graph showed that there was a broad range in water deficit from -1300 mm to 1000 mm. Furthermore, ecosystems outside US showed different $E_a$ and water deficit compared to Stephenson’s diagram. For example, $E_a$ of a cypress forest in Japan ranged from 720 to 750 mm, which is higher than Stephenson’s guideline (240 to 600 mm) (Figure 4.10) (Kosugi et al. 2007). For a wet temperate grassland in Japan, annual $E_a$ reached 800 mm, which is much higher than the annual grassland of this study and cannot be classified within Stephenson’s framework. It should be noted that Stephenson’s classification is for North America, so it may not be applicable outside North America. It is expected that the growing FLUXNET database across diverse ecosystems can contribute to revising and refining the PFTs schemes, and it will clearly help to scale-up flux data into regional and continental scales.
Figure 4. 10. The relationships between annual water deficit ($E_p$-Ppt) and annual actual $E$. $E_p$ and Ppt are potential $E$ and precipitation. Data for a temperate deciduous forest from Wilson and Baldocchi (2000), a cypress forest from Kosugi et al (2007), woody savanna from Baldocchi et al (2004) with unpublished data, a wet temperate grassland from Li et al (2005), and an annual grassland from this study. $E_p$ was calculated from $E_{eq}$ times 1.24.

4.5. Summary and conclusions

In this study, we reported on the interannual variability of $E$ and energy fluxes over an annual grassland growing in the Mediterranean-type climate in California using a 6-year flux measurement. The Mediterranean climate system of the study site has two distinct seasons. One is a wet period during winter with ample water and low solar radiation. The other is a dry period in summer with scarce soil water and high levels of solar radiation. Consequently, ecosystem $E$ experiences both water-limited and energy-limited periods during the year. In the energy-limited period, the majority of $E$ scaled positively with $R_g$ and was confined by $E_p$. In the water-limited period, however, most $E$ was down-regulated by stomatal closure and scaled negatively with $R_g$. In general, high rainfall in wet season did not lead to high $E$ because of the marginal available energy. Therefore, the annual $E$ amount of this ecosystem was not sensitive to annual precipitation amount. Rather, the lifespan of the annual grassland that was coincident with the
timing of rainfall was critical in determining the hydrological growing season length and the amount of annual $E$. Rainfall in May and June was especially critical in extending the growing season and $E$. We expect that the cloud cover and precipitation regime in May and June will play a key role in modulating annual $E$ amount in this ecosystem in future years. $G_s$ scaled tightly with $\alpha$ regardless of interannual and seasonal variability of precipitation, $E$, and $R_g$, implying that this relationship may be used to discern PFTs. Additionally, we showed that long-term flux measurement can be used to test classification of PFTs, which is critical to upscale flux measurements into regional and continental scales.
Chapter 5: Testing the performance of a novel spectral reflectance sensor, built with light emitting diodes (LEDs), to monitor ecosystem metabolism, structure and function

5.1. Introduction

A central theme shared between flux community and remote sensing community revolves around linking spectral reflectance indices with vegetation structure (e.g. leaf area index (LAI)), function (e.g. nitrogen (N), phenology) and metabolism (e.g. gross primary productivity, evaporation) (Baldocchi et al. 1996; Gamon et al. 2006b; Running et al. 1999). The reflectance of sunlight in the visible and near infrared portions of the electromagnetic spectrum is correlated with vegetation status, development and growth, and is monitored for this reason in remote sensing of terrestrial vegetation. Spectral reflectance measured from air- and space-borne platforms covers broad areas repeatedly, but such measurements are prone to contamination by atmospheric effects (e.g. aerosol, clouds etc) (Kobayashi and Dye 2005). Thus, continuous observation of vegetation reflectance in-situ is warranted to better understand the vegetation status with direct high spatial and temporal resolution data (Gamon et al. 2006b).

Efforts to monitor vegetation spectral reflectance continuously have been initiated in several studies, including sophisticated multi-angle spectrometers (Hilker et al. 2007; Leuning et al. 2006), a rotating hemispherical spectrometer (Nagai et al. 2010) and a dual detector spectrometer attached to a mobile tram system (Gamon et al. 2006a). However, commercially available spectrometers used in the previous studies are expensive. Recently, a narrow-band spectrometer equipped with photodiodes in a moderate cost ($720 per pair) was reported (Garrity et al. 2010). Alternatively, light emitting diodes (LEDs) - inexpensive, small and stable light sources - have the potential to measure vegetation spectral reflectance for a wide range of narrow and selective wavebands (RayChaudhuri and Sen 2009).

LEDs emit incoherent light in narrow wavelength bands and are ubiquitous as a light source in traffic lights, lamps and television. In their reverse mode, LEDs generate a current that is proportional to incident radiance in selected spectral regions. Atmospheric scientists applied this principle to monitor precipitable water over ten years with very reliable stability (Mims 1992, 2002). However, the application of LEDs to monitor vegetation reflectance is at the very beginning.

LEDs have the potential to provide multi-band reflectance because commercially available LEDs exist for many wavelength bands, including ultraviolet, blue, green, red, and near infrared.
Valuable information can be inferred from multispectral reflectance in ecological studies because numerous aspects of ecosystem structure, function and metabolism show wavelength-specific responses (Asner and Martin 2009; Sellers 1985; Ustin et al. 2004). Thus it is possible to construct a spectrometer that combines LEDs covering different wavelength bands to monitor specific ecological processes.

In this study, we examine the performance of a novel LED-spectrometer that we designed, built and tested for 3.5 years in an annual grassland of California. To investigate how the multi-year data of the instrument allows us to answer a variety of remote sensing science questions on its performance and utility to predict variables related to vegetation structure, function and metabolism, we address four scientific questions including: 1) how does solar zenith angle influence spectral reflectance and NDVI of the LED-spectrometer? 2) can this new instrument monitor seasonal and interannual variations of vegetation spectral reflectance? 3) can the new instrument track temporal changes in ecosystem phenology? and 4) can the instrument be used to estimate the functional dependence of canopy photosynthesis, LAI and N for an annual grassland?

5.2. Methods

5.2.1. Study site

The study site is an annual grassland (Vaira Ranch, latitude: 38.413°N; longitude: 120.951°W; altitude: 129 m) in central California, USA (Ryu et al. 2008). It experiences a Mediterranean-type climate with dry hot summers and wet mild winters. Precipitation is concentrated between November and May with little precipitation during the summer (Figure 5.1a). The grass is dominated by cool-season C3 annual species, including Brachypodium distachyon L., and Hypochaeris glabra L. (Ma et al. 2007; Xu and Baldocchi 2004). Grasses usually germinate around November with the beginning of winter rainfall and grow between December and May, followed by quick senescence with the onset of the summer drought.

5.2.2. LED-spectrometer

5.2.2.1. Development

We developed the LED-spectrometer in 2004. We selected two bands of LEDs that include red (peak sensitivity: 646 nm, full width half maximum (FWHM): 56 nm, field of view (FOV): 120 degree, model: Lumex SSL-LX5093SRD, Palatine, IL) and near-infrared (peak sensitivity: 843 nm, FWHM: 72 nm, FOV: 80 degree, model: Fairchild F5E3, San Jose, CA) (Figure 5.1). Among the available wavebands in off-the-shelf LEDs, we selected the wavebands that are comparable with MODIS red (620-670 nm) and near infrared (NIR) (841-876 nm) wavebands.
which are used to calculate MODIS normalized vegetation index (NDVI) (Huete et al. 2002; Tucker 1979):

\[
NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}}
\]

(5. 1)

where \( \rho_{NIR} \) and \( \rho_{RED} \) are reflectance of NIR and red bands, respectively.

Figure 5. 1. Spectral response of red and near infrared LEDs

We used a diffuser material (Teflon®, DuPont, Wilmington, DE, USA) several millimeters above the LED-spectrometer to improve the cosine response (Figures A5. 2 and A5. 3). Thus, the FOV of the LED-spectrometer was ~180 degrees. The LED-spectrometer consists of four channels: two up and two downward-looking pairs of red and NIR channels measuring incoming and reflected photons, respectively. This design feature enables us to avoid using a white reflectance reference panel, which would get dirty and fouled with long term use. Total cost of one LED-spectrometer was ~ 150 $. A more technical description of the instrument is provided as supplementary material (Appendices 5. 1 to 5. 3). For field application, we installed the instrument on a horizontal boom 3 m above the ground surface. A data logger (Model CR23X,
Campbell Sci., Inc., CSI, Logan Utah) sampled irradiance at the four channels every 10 seconds and stored half-hour mean values.

5.2.2.2. Calibration using hyperspectral reflectance measurements

To calibrate and evaluate the stability of the LED-spectrometer, we regularly measured hyperspectral reflectance (range: 400 to 900 nm, FWHM: 1.3 nm) at the canopy scale with a hand-held spectrometer (USB2000, Ocean Optics Inc, Dunedin, FL). The spectrometer was mounted on a portable tripod with an attached aluminum boom, connected to a 2 m fiber optic transmitter and a cosine-corrector (Teflon®) with a 180 degree FOV. Measurement height above the grass canopy was kept at 1 m. Vegetation spectral reflectance was obtained by measuring both incoming and reflected irradiance spectra with the same spectrometer in sequence, using the same integration time and instrument configuration. We randomly sampled at least three points within a 5-m radius of the LED-spectrometer and then averaged the spectral reflectance of the samples. The red and NIR bands of the hand-held spectrometer were determined to be the same with the red and NIR bands in the LEDs (Figure 5.1). We found that there has been no significant drift in the two bands by comparing the mean±95% confidence intervals of the slopes for the four years ($p>0.05$, linear regression that forces to pass the origin) (Figure 5.2). Finally, we calibrated the raw reflectance of the LED-spectrometer by dividing by 1.33 (red band, the slope of Figure 5.2a) and 1.68 (NIR band, the slope of Figure 5.2b).
Figure 5.2. Calibration of LEDs derived NDVI sensor for red and NIR bands against a handheld spectrometer measurements.

5.2.3. Ancillary measurements
We regularly measured grass LAI during the active period by harvesting four sample plots (0.25 m × 0.25 m). Leaf nitrogen content of grass (% of dry weight) was determined with a plant chemical analyzer at the Center for Stable Isotope Biogeochemistry, UC Berkeley. We estimated canopy photosynthesis using the eddy covariance method by partitioning day and night measurements of net ecosystem carbon exchange (i.e. net ecosystem exchange minus ecosystem respiration) (Ma et al. 2007). We recorded grass green-up and senescence dates when 90% of grass community was either alive or dead, respectively, based on weekly to bi-weekly visual inspections.

5. 3. Results and Discussion

5. 3. 1. Effects of the solar zenith angles on the red, NIR reflectance and NDVI of the LED-spectrometer

The dependence of the spectral reflectance on the solar zenith angle is crucial to understand seasonal variations of spectral reflectance and vegetation indices. For example, Sims et al (2006) reported that the diurnal variation of NDVI was larger than the seasonal variation of NDVI in a chaparral site, and the seasonal variations of NDVI in the local noon and solar zenith angle at 60 degree were out-of-phase and showed different magnitudes. In our study site, we found that there was weak diurnal variation in the red reflectance (Figure 5. 3a) except for the peak grass photosynthesis period when showing almost constant reflectance during the daytime due to high absorption of the red light by grass (DOY100 in the Figure 5. 3a, also see Fig 5. 5a to compare with grass photosynthesis). The NIR reflectance showed greater diurnal variation over the course of the year (Figure 5. 3b). However, the NDVI did not show pronounced diurnal variation (Figure 5. 3c) contrary to the Sims et al (2006). We presume that the land surface heterogeneity would explain the discrepancy. The vegetation distribution was clumped and half of the surface was bare soil at the study site of Sims et al (2006) whereas the grass community was homogeneous in the current study site. Next, we compared the NDVI, red and NIR reflectance between the local noon and fixed solar zenith angle at 60 degree in the year of 2007 (Figure 5. 3 d-f). Both red and NIR reflectance showed large difference in their magnitudes between the two cases in the summer when the grass is dead and solar zenith angle is much lower than 60 degree. However, the two cases were in-phase and shared important transition points (e.g. peak timings, reflection points). Again, the NDVI was not sensitive to the solar zenith angle and showed similar seasonal pattern between the two cases (Figure 5. 3f).
We tested the impact of sky condition on the spectral reflectance and NDVI (Figure 5.3g-i). As expected, both red and NIR reflectance were strongly related with the solar zenith angle only on the clear sky day (DOY 112), not on the cloudy sky day (DOY 111). Overall, the NDVI was slightly higher for the cloudy day than the clear sky day (Figure 5.3i). It is notable that the clear and cloudy lines intersected at ~ 50 degree of solar zenith angle (Figure 5.3g, h), indicating that spectral reflectance of cloudy condition could be higher or lower than that of clear sky depending on the solar zenith angle. For example, in the grey box of the Figure 5.3e, the deviated points from the general pattern were cloudy sky days. For those cloudy days, the local noon data (20-40 degree of solar zenith angle in this period) and the data at the 60 degree of solar zenith angle presented the opposite signs from the general pattern because of the solar zenith angle. The LED-
spectrometer allows us to investigate the effect of sky condition on the spectral reflectance which is hard to obtain from the satellite or periodic manual sampling. We conclude that the red and NIR reflectance are moderately to strongly related with solar zenith angles, but the NDVI is not sensitive to the solar zenith angle in the study site.

5.3.2. Seasonal and interannual variation of spectral reflectance

The red and NIR reflectance at local noon showed pronounced seasonal and inter-annual variability (Figure 5.4b). The NDVI ranged from 0.2 to 0.85 as LAI varied from near zero to 2.5, thus the LED-spectrometer detected a broad range in vegetation condition. Healthy green vegetation absorbs most of the incident visible radiation, particularly in the red portion of the spectrum, and reflects and transmits most of the incident NIR. Consequently, the temporal variation of the red and NIR reflectance was mirrored when grasses were active. Notably, the first and second rain pulses after the prolonged summer drought caused an abrupt decrease of the spectral reflectance of both wavelength bands.
Figure 5.4. (a) Time series of daily rainfall. (b) Red and near infrared reflectance (local noon) of LED-spectrometer from 2006 Jan to 2009 June. Vertical arrows indicate the first and second rainfalls in the transition between dry and wet seasons. Horizontal arrows indicate an example of the cloudy condition. (c) Time series of LEDs derived NDVI (midday) and leaf area index (weekly to bi-weekly when grass is alive) measured using harvest method. All LEDs reflectance was calculated at local noon time measurements. The vertical dashed (solid) lines indicate the dates of grass offset (onset) (See 3.2. for details).

The sensor was able to track inter-annual variations in canopy structure as well. We observed the lowest LAI (Figure 5.4b) and canopy photosynthesis (Figure 5.5b) in 2008, which recorded the lowest rainfall among the four years (Figure 5.4a). The NDVI signal agreed with those observations by showing the lowest peak NDVI value in 2008 (Figure 5.4b). The NIR reflectance in the 2008 spring was the lowest among the four-year springs because of the lowest LAI (Figure 5.1b). Dead grass is very bright (higher reflectance) compared to the darker
background soil. Thus less grass production in the previous growing season led to lower reflectance (i.e. higher energy absorption) at both red and NIR bands during the dry summer 2008 than the other years ($p<0.05$, Tukey-Kramer test). The previous studies conducted at the same site showed that maximum grass LAI is very sensitive to the rainfall amount in the spring (Ma et al. 2007; Ryu et al. 2008a). Thus the spring rainfall would be the main driver to control the carbon sequestration in the spring and the land surface radiation balance during the summer. Continuous monitoring of the vegetation spectral reflectance will be useful to test this hypothesis. The above analysis and interpretations are valid even using the red and NIR reflectance data at 60 degree of solar zenith angle.

5.3.3. Extracting key phenological events of grass community

Phenology is the timing of biological events (e.g. leaf-on, leaf-off). There has been pressing need to monitor phenology (Morisette et al. 2009) because growing season length modulates annual carbon uptake (Baldocchi et al. 2001a; Black et al. 2000; Carrara et al. 2003) and evaporation (Ryu et al. 2008a) of ecosystems and because phenology produces an independent signature of climate change (Parmesan and Yohe 2003; Peñuelas et al. 2009).

LED-based reflectance clearly showed the phenological cycles of the grass community (Figure 5.4a and b). We identified the dates of leaf-on when red (NIR) reflectance abruptly decreases (increases) after autumn rainfall (vertically solid lines in Figure 5.1b and c), which indicates the onset of photosynthesis. These patterns showed good agreement with weekly or bi-weekly field observation (absolute mean bias error was $5.3\pm0.4$ days (mean ± standard error)) (Table 5.1).

We determined the leaf-off dates as averages of when the NIR reflectance is at its minimum and the slope of the red reflectance abruptly changes (vertically dashed lines in Figure 5.4a and b), indicating that the grass LAI is at a minimum. The calculated leaf-off dates also showed good agreement with field observation (absolute mean bias error was $4.2\pm1.6$ days). Leaf-on and leaf-off dates, derived from the LED-spectrometer, defined the seasonality of LAI values well (Figure 5.4c). Strengths of using the LED-spectrometer for phenological research include general applicability regardless of weather conditions and high temporal resolution. Satellite-based phenology studies have coarse temporal resolutions, and thus the interpolation of a time series into daily resolution remains a critical issue (Morisette et al. 2009; White et al. 2009).

Table 5.1. Leaf-on and leaf-off dates recorded from field observation (weekly to bi-weekly) and LEDs system

| leaf-on dates (day of year) | leaf-off dates (day of year) |
5.3.4. Investigating seasonality of canopy photosynthesis

Canopy photosynthesis is an essential variable to understand the interactions between ecosystem and climate, yet measuring canopy photosynthesis has been limited due to expensive instrument systems (e.g. eddy covariance method (Baldocchi 2008)) or labor-intensive ecosystem inventory (Clark et al. 2001). Alternatively, the remote sensing community has used normalized difference vegetation indices widely to infer canopy photosynthesis (Fung et al. 1987; Gamon et al. 1992; Gitelson et al. 2003; Sellers 1985); remotely sensed vegetation index, like NDVI, has to be used with caution because NDVI is known to saturated where LAI is greater than 3 (Sellers 1985). For the California grassland, we found that NDVI values, derived from the LED-spectrometer, explained 91% of variance in the canopy photosynthesis over 3.5 year (Figure 5. 5b). At our study site, LAI is typically less than 3 and most canopy photosynthesis happens in the wet period. Consequently, NDVI is a good indicator to estimate canopy photosynthesis of annual grasslands as reported by Gamon et al (1995).

An exponential relation between NDVI and canopy photosynthesis is notable over the course of the growing season (Nov-May) (Figure 5. 5b). This non-linearity occurs because canopy photosynthesis is a multiplicative function of two processes upon which NDVI is related; these are the fraction of absorbed PAR (fPAR) and light use efficiency (Goward and Huemmrich 1992; Sellers 1985; Sims et al. 2006). Consequently, the increase in the first derivative of the exponential curve with NDVI is a reflection of the combined increase in leaf area index, fPAR and light use efficiency during the active growth period when soil moisture is ample. In contrast, the period when NDVI is low corresponds with the severe drought period when leaf area index, fPAR and light use efficiency are low. We conclude that the exponential shape NDVI-photosynthesis relationship may be an inherent property of seasonally-droughted grassland ecosystems when LAI is less than 3.
Figure 5. 5. (a) Time series of daily canopy photosynthesis from eddy flux tower and midday LEDs derived NDVI in 2007. (b) Scatter plot between 8-day mean of midday LEDs derived NDVI and 8-day mean canopy photosynthesis from 2006 January to 2009 July. Dashed line indicates 95% confidence interval on the linear regression (solid line).
5.3.5 Exploring optimal LED wavelengths for improved monitoring of ecosystem structure and metabolism

To explore the potential of other spectral regions to monitor canopy photosynthesis, LAI and leaf nitrogen, we compute a continuum of normalized difference spectral indices (i.e. Eq 5.1 using two different wavebands) (Inoue et al. 2008; le Maire et al. 2008), which were measured with the hand-held hyper-spectral radiometer, and correlate these indices with independent variables like canopy photosynthesis. We found that a normalized difference spectral index that combines green (~550 nm) and NIR (730–830 nm) showed the highest correlation with canopy photosynthesis (Figure 5.6a) and LAI (Figure 5.6b). Both 550 nm and the 730-830 nm regions occur at the edges of chlorophyll absorption bands and are sensitive indicators of vegetation. In particular, it is well known that the green band is much more sensitive to chlorophyll-a concentration than the chlorophyll-a absorption band (~670 nm) (Gitelson et al. 1996; Yoder and Waring 1994). Because the chlorophyll concentration is linearly related with potential photosynthesis (Waring et al. 1995; Zhang et al. 2009), the use of the green band has the potential to link with canopy photosynthesis. Also the region of photochemical reflectance index (520 nm and 570 nm) revealed a moderate correlation with canopy photosynthesis. We believe it is related with seasonal water stress and fluorescence (Gammon et al. 1997; Grace et al. 2007). On the other hand, we found that leaf nitrogen showed high correlation with specific NIR bands (800-850 nm and ~780 nm) or between the red edge (~700 nm) and blue (~480 nm) or green (~520 and ~580 nm) bands. The NIR region might include nitrogen information because leaves with higher nitrogen concentration are associated with higher leaf photosynthesis capacity (Field and Mooney 1986), the ratio of leaf mesophyll cell surface area exposed to intercellular air spaces per unit leaf area to facilitate CO2 diffusion, which correlated with reflectance at NIR (Hollinger et al. 2009; Ollinger et al. 2008; Slaton et al. 2001). The red edge region is sensitive to chlorophyll-a concentration which is usually scaled with nitrogen content. The area of wavelengths that the LED-spectrometer covers (white rectangular box in Figure 5.6(a)-(c)) did not show the highest correlation with these three variables. We found that the highest correlation regions in the Fig 6(a)-(c) can be covered by commercially available LEDs. Based on this new information and developments in variety of commercial LEDs we have the possibility to redesign the LED-spectrometer with low cost so it can target these high correlation spots.
Figure 5. 6. Contour maps of correlation coefficient ($r$) between normalized difference spectral indices using two wavelengths (x and y axis) and (a) canopy photosynthesis ($n=33$), (b) leaf area index ($n=33$), and (c) leaf nitrogen ($n=10$). White rectangular box indicates the spectral region of LEDs derived NDVI instrument.

5. 3. 6. Broader implications

Based on a variety of spectral wavebands, inexpensive price and reliable performance, the LED-spectrometer has the potential for wide-spread application on many remote sensing and ecological topics. Firstly, the LED-spectrometer has the potential to replace expensive four-bands radiometer (Fensholt and Sandholt 2005) and be deployed widely among a number of long-term ecosystem monitoring programs like the global spectral reflectance network (SpecNet) (Gamon et al. 2006b), Long Term Ecological Research Network (http://www.lternet.edu/), National Ecological Observatory Network (http://www.neoninc.org/), global eddy flux tower network-FLUXNET (Baldocchi et al. 2001a). Secondly, deployment of the LED-spectrometer gives investigators the potential to infer ecosystem metabolism, structure and function in treatment plots that may be too small for application of the eddy covariance method or in plots where repeated sample is too expensive, such as in Free-Air Carbon Dioxide Enrichment (FACE) studies (Norby et al. 2005), biodiversity (Tilman et al. 2001) and biofuel (Heaton et al. 2008) field trials and ecosystem manipulation experiments. Finally, the LED-spectrometer could be instrumental in the educational realm as well. Students have used an LED-spectrometer to monitor atmospheric turbidity in the Global Learning and Observations to Benefit the Environment Program (Mims 1999). Here, we recommend that students use two sets of LED-spectrometers (upward and downward), to learn how vegetation reflectance changes with different surface properties.

5. 4. Summary and Conclusions

To link remote sensing with ecosystem fluxes, there are pressing needs to develop inexpensive but reliable spectrometers. In this study, we reported on a novel, inexpensive spectral sensor equipped with LEDs. Based on the 3.5 years of data from an annual grassland, we found that the LED-spectrometer is able to monitor daily to interannual variations of vegetation spectral reflectances. The continuous measurements of spectral reflectance enabled us to track the ecosystem phenology (5.3 and 4.2 days of the mean bias errors at leaf-on and leaf-off dates, respectively) and estimate canopy photosynthesis ($r^2=0.91$). The LED-spectrometer is a cost-effective solution to monitor vegetation structure and metabolism variables with high flexibility in the wavebands selection than other spectrometers. We believe that the LED-spectrometer can be used in a variety of ecological applications.
6. 1. Introduction

Evapotranspiration ($E$) is a major component of the terrestrial hydrological cycle (ca. 60% of precipitation) (Trenberth et al. 2007). It controls land-atmosphere feedbacks and constitutes an important source of water vapor to the atmosphere (Raupach 1998). In turn, atmospheric water vapor is the most significant greenhouse gas and thus plays a fundamental role in weather and climate (Held and Soden 2000). Understanding $E$ is important for socio-economic reasons, such as regulating available water for human use (Brauman et al. 2007). Thus, there have been diverse efforts to regularly monitor $E$ in a regional scale using satellite remote sensing imagery (Diak et al. 2004; Nishida et al. 2003).

The applicability of remote sensing-based estimates of $E$ is hampered because satellites have limited temporal coverage, resulting in snapshots of $E$ at a particular point in space and time. Thus, it is a challenge to compare $E$ estimates from different sites and taken at different times of the day. For practical purposes, time-integrated $E$ is more useful for managing water resources and for comparison with accumulated precipitation. Several methods have been proposed to upscale snapshot estimates to time-integrated values. One approach is to assume that the evaporative fraction, $EF$, (the ratio of latent heat flux, $\lambda E$, to available energy, $A$, which is equal to the net radiation ($R_n$) minus the soil heat flux ($G$)) is conservative during daytime, so daytime total $E$ can be estimated by multiplying $EF$ and daytime integrated $A$ (Brutsaert and Sugita 1992). Anderson et al. (2007) further developed this idea by coupling a planetary boundary layer model with two snapshots in the morning from Geostationary Operational Environmental Satellites (GOES) for calculating instantaneous $\lambda E$ and $EF$, and finally extrapolated these values to a daily scale using hourly $A$ derived from GOES. However, it is difficult to accurately estimate daytime $R_n$ and $G$ from remote sensing, and $EF$ varies considerably during daytime depending on soil moisture status and leaf area index (Leuning et al. 2004).

Recently, several MODIS global $\lambda E$ algorithms have been proposed (Cleugh et al. 2007; Leuning et al. 2008; Mu et al. 2007). Even though the algorithms were well validated against eddy covariance (EC) measurements, all forcing data were derived from daily global meteorological data ($R_n$, humidity, and temperature) or MODIS land products (8- or 16-day composites). This approach has the advantage of providing spatially and temporally continuous gridded data, with the limitation of coarse spatial (10 km) and temporal (daily) resolution that make it difficult to match with satellite snapshots. Now that radiation, humidity and temperature data are available from MODIS snapshots (Houborg et al. 2007; Ryu et al. 2008b), estimates of $\lambda E$ using only MODIS data might be achieved if temporal upscaling issue is resolved.
One alternative is to find and test a scaling factor between an instantaneous (i.e. single-hour) $\lambda E$ value and the mean value of 24-h $\lambda E$ for a period of days (e.g. 8-day) using EC data. The basic idea is that average instantaneous $\lambda E$ of satellite overpass time (e.g. 1000 to 1100hh for MODIS onboard Terra) over several days (e.g. 8-day) could be upscaled to 8-day mean daily (24-h) value if a linear relationship between them exists. Sims et al. (2005) applied a similar approach for the case of gross primary productivity (GPP).

Here, we present a temporal upscaling scheme from instantaneous measurements to 8-day mean daily (24-h) $\lambda E$ estimates. The objectives are: 1) test the ratio ($\lambda E_{\text{hour}} / \lambda E_{\text{day}}$) variation over time for different plant functional types (PFTs), 2) analyze linear regression statistics using a meta-analysis approach, and 3) investigate the effects of clouds on this scheme. Finally, we propose an upscaling factor based on data from 26 FLUXNET sites that may be applicable to imagery from satellites such as MODIS and GOES with higher re-visit frequency (at least one visit per day).

The novelties of our work over that of Sims et al. (2005) are: a) the clouds effect was taken into account, and b) we extended mid-day hours to include 1000-1400hh for temporal scaling of $\lambda E$.

6.2. Methods

6.2.1. Sites description and flux data processing

We analyzed $\lambda E$ data from 26 sites including seven PFTs ranging from boreal to tropical climatic zones (Table 6.1). Data were drawn from the LaThuile 2008 FLUXNET dataset (www.fluxdata.org) and each site had a minimum of 330 days per year after gap-filling (marginal distribution sampling method) and quality control following Reichstein et al. (2005). At least three sites for each PFT were selected and one year of data for each site was analyzed. Detailed descriptions of study sites and flux measurements are given in references listed in Table A6.1. Data gaps were filled using the marginal distribution sampling method (Reichstein et al. 2005). Mid-day hourly means (i.e., 1000-1100hh; 1100-1200hh; 1200-1300hh; 1300-1400hh) of $\lambda E$ from flux towers were calculated to correspond with potential overpass times of the MODIS Terra and Aqua satellites. Overpass times vary among sites because of changing sensor view angle and orbital mode (i.e. ascending or descending) (Masuoka et al. 1998). Means for each mid-day hour were averaged over a 8-day periods corresponding to the cycle of MODIS global coverage (Masuoka et al. 1998).

Linear regressions with an intercept through the origin were calculated by comparing 8-day means of $\lambda E$, averaged over 24-hours, against mid-day single-hourly means (i.e., 1000-1100hh; 1100-1200hh; 1200-1300hh; 1300-1400hh) of $\lambda E$ for the corresponding 8-day periods using MATLAB R2007b (The MathWorks, Inc.). We then used MetaWin 2 for a meta-analysis approach with MetaWin 2.1 (Sinauer Associates, Inc.) (Rosenberg et al. 2000) to calculate the standard error-weighted mean slope. The site-specific slopes ($E^i$) with their standard errors ($S_E^i$)
were generated from linear regression analysis. Slopes in each categorical group (\( \bar{E} \) for PFT and hourly step) were weighted by the inverse of standard errors of the slopes (\( w_i = 1/s_{E_i} \), Eq 6.1) to generate a mean slope. We calculated 95% confidence intervals (CI) around the mean slope, for comparison between the categories to test for significant differences (Eq 6.2):

\[
\bar{E} = \frac{\sum_{i=1}^{n} w_i E_i}{\sum_{i=1}^{n} w_i}
\]

(6.1)

\[
CI = \bar{E} \pm t_{\alpha/2(n-1)} \times s_E
\]

(6.2)

where \( t \) is the two-tailed critical value from \( t \)-distribution at the critical level \( \alpha \), and \( s_E \) is standard error of mean slope (\( 1/\sum_{i=1}^{n} w_i \)).

Table 6.1. Site information. CRO: crop, DBF: deciduous broadleaved forest, EBF: evergreen broadleaved forest, ENF: evergreen needle leaved forest. GRA: grassland, MF: mixed forest, WSA: woody savanna*.

<table>
<thead>
<tr>
<th>PFT</th>
<th>Site ID</th>
<th>Lat</th>
<th>Lon</th>
<th>Year</th>
<th>Climate</th>
</tr>
</thead>
<tbody>
<tr>
<td>CRO</td>
<td>US-Bo1</td>
<td>40.0</td>
<td>-88.3</td>
<td>1998</td>
<td>Temperate</td>
</tr>
<tr>
<td>DE-Geb</td>
<td>51.1</td>
<td>10.9</td>
<td>2004</td>
<td>Temperate</td>
<td></td>
</tr>
<tr>
<td>JP-Mas</td>
<td>36.1</td>
<td>140.0</td>
<td>2002</td>
<td>Temperate</td>
<td></td>
</tr>
<tr>
<td>KR-Hnm</td>
<td>34.6</td>
<td>126.6</td>
<td>2006</td>
<td>Temperate</td>
<td></td>
</tr>
<tr>
<td>DBF</td>
<td>CA-Oas</td>
<td>53.6</td>
<td>-106.2</td>
<td>2004</td>
<td>Boreal</td>
</tr>
<tr>
<td>DE-Hai</td>
<td>51.1</td>
<td>10.5</td>
<td>2004</td>
<td>Temperate</td>
<td></td>
</tr>
<tr>
<td>US-MOz</td>
<td>38.7</td>
<td>-92.2</td>
<td>2005</td>
<td>Sub-tropical, Mediterranean</td>
<td></td>
</tr>
<tr>
<td>EBF</td>
<td>FR-Pue</td>
<td>43.7</td>
<td>3.6</td>
<td>2006</td>
<td>Sub-tropical, Mediterranean</td>
</tr>
<tr>
<td>IT-Cpz</td>
<td>41.7</td>
<td>12.4</td>
<td>2004</td>
<td>Sub-tropical, Mediterranean</td>
<td></td>
</tr>
<tr>
<td>AU-Tum</td>
<td>-35.7</td>
<td>148.2</td>
<td>2003</td>
<td>Temperate</td>
<td></td>
</tr>
<tr>
<td>ID-Pag</td>
<td>2.3</td>
<td>114.0</td>
<td>2002</td>
<td>Tropical</td>
<td></td>
</tr>
<tr>
<td>ENF</td>
<td>FI-Hyy</td>
<td>61.8</td>
<td>24.3</td>
<td>2006</td>
<td>Boreal</td>
</tr>
</tbody>
</table>
9.2

9.2.2. Clearness index

To investigate the degree of cloudiness in each site, clearness index ($k_i$) is introduced. Clear skies are defined when $k_i > 0.6$ (Reindl et al., (1990)). Here $k_i$ is defined according to (Liu and Jordan 1960) as:

$$k_i = \frac{S}{S_e}$$  \hspace{1cm} (6. 3)

$$S_e = S_{sc}[1 + 0.033 \cos(2 \pi t_d / 365)] \cos \beta$$  \hspace{1cm} (6. 4)

where $S$ is observed incoming global radiation $R_g$, $S_e$ is the extraterrestrial irradiance on a plane parallel to the Earth’s surface, $S_{sc}$ is the solar constant (1370 W m$^{-2}$), $t_d$ is the day of year, and $\beta$ is solar zenith angle that is calculated following Michalsky (1988). The value of $k_i$ was calculated half-hourly, and averaged to provide hourly values.

6. 3. Results and discussions

6. 3. 1. The ratio of single-hourly $\lambda E$ sum to daily $\lambda E$ sum
As a first step for temporal upscaling, the ratios of single-hourly $\lambda E$ sum to daily $\lambda E$ sum were investigated (Figure 6. 1). Each selected site showed different mean diel patterns of $\lambda E$ for each month (left hand column of Figure 6. 1). The ratios (right hand column of Figure 6. 1) did not vary much for each month and, importantly, they were fairly stable around 0.11 ($\pm$0.013 standard deviation) during potential MODIS overpass times (1000 to 1400hh). The ratio increased steadily from 1000 to 1400hh at CA-Oas site in January (Figure 6. 1b). It is assumed that the error arising from this non-conservative ratio would not be substantial in estimating daily $\lambda E$ because $\lambda E$ was close to zero in this month (Figure 6. 1b left). The conservative ratio during the MODIS overpass time enables a daily (24-h) value to be determined from each single-hourly value. For avoiding numerical instability, the sum ratio was used instead of the mean ratio shown in Figure A6. 1 and Table 6. 2.
Figure 6.1. Monthly mean diurnal variation of hourly $\lambda E$ (left column) and the ratio of hourly sum to daily sum for seven sites. One site for each plant functional type (PFT) was selected. The vertical blue dashed lines in the right column indicate 1100 and 1400hh corresponding to MODIS overpass time. 1100hh represents an average from 1000 to 1100hh. Abbreviations of PFTs are the same as in Table 6.1.

6.3.2. Statistical analysis to obtain upscaling factor
We found a strong linear relationship ($r^2>0.94$) between single-hourly mean and 8-day mean daily (24-h) $\lambda E$ for each PFTs and each of the 4 hours categories (see Figure A6. 1). Table 6. 2 shows the statistics of upscaling factors for each hourly time step and PFT. There were no significant differences within hours and within PFTs or between hours and PFTs. Therefore, we report a mean slope using all categories (hours or PFTs) of 0.370 (95% CI: 0.354, 0.385), which is equivalent with 0.11 (=$1/(0.370\times24)$) of the ratio of hourly $\lambda E$ sum to daily $\lambda E$ sum (See section 3.1 and Figure 6. 1).

Table 6. 2. Statistics for linear regression of 8-day average $\lambda E$ versus hourly-average $\lambda E$ for data grouped by hour and PFT. The mean slope is statistically the same for hours and PFTs categories. The abbreviations of PFTs are the same as in Table 6. 1.

<table>
<thead>
<tr>
<th></th>
<th>Degree of freedom</th>
<th>Mean slope</th>
<th>95% confidence interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hours</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10 to 11</td>
<td>26</td>
<td>0.405</td>
<td>0.372 to 0.438</td>
</tr>
<tr>
<td>11 to 12</td>
<td>26</td>
<td>0.364</td>
<td>0.332 to 0.396</td>
</tr>
<tr>
<td>12 to 13</td>
<td>26</td>
<td>0.353</td>
<td>0.321 to 0.385</td>
</tr>
<tr>
<td>13 to 14</td>
<td>26</td>
<td>0.359</td>
<td>0.327 to 0.391</td>
</tr>
<tr>
<td>PFTs</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CRO</td>
<td>16</td>
<td>0.362</td>
<td>0.318 to 0.405</td>
</tr>
<tr>
<td>DBF</td>
<td>12</td>
<td>0.373</td>
<td>0.322 to 0.424</td>
</tr>
<tr>
<td>EBF</td>
<td>16</td>
<td>0.349</td>
<td>0.308 to 0.390</td>
</tr>
<tr>
<td>ENF</td>
<td>12</td>
<td>0.396</td>
<td>0.342 to 0.449</td>
</tr>
<tr>
<td>GRA</td>
<td>20</td>
<td>0.368</td>
<td>0.333 to 0.402</td>
</tr>
<tr>
<td>MF</td>
<td>12</td>
<td>0.374</td>
<td>0.322 to 0.426</td>
</tr>
<tr>
<td>WSA</td>
<td>16</td>
<td>0.380</td>
<td>0.334 to 0.425</td>
</tr>
<tr>
<td>Mean slope</td>
<td>103</td>
<td>0.370</td>
<td>0.354 to 0.385</td>
</tr>
</tbody>
</table>

6.3.3. Clouds and error sources

Our approach assumes that at least one estimate of $\lambda E$ per day is available. Generally, a maximum of two points can be obtained each day in MODIS, but with missing land surface information under cloudy skies. If only clear-sky daytime data are selected and averaged over an 8-day period, then multiplying the average value by 0.370 can overestimate 8-day mean $\lambda E$ values. This is contrary to the relatively minor effect of clouds on estimates of GPP because light use efficiency tends to increase under cloudy sky (Sims et al. 2005). Figure 6. 2 (a) shows that higher $k_t$ is related to the higher ratio of $\lambda E_{clear}/\lambda E_{all}$. For example, temperate climate zones are
substantially influenced by clouds and about half of the yearly $\lambda E$ occurred on cloudy days, which affect remote sensing applications.

Figure 6. 2. (a) Scatterplot of the ratio of $\lambda E$ sum under clear sky (clearness index $>0.6$) to $\lambda E$ sum for all sky conditions versus the yearly average clearness index from 1000 to 1400hh. (b) Scatterplot of the ratio of cloudy $\lambda E$ to clear $\lambda E$ versus the ratio of cloudy $R_g$ to clear $R_g$ conditions. A clear-sky day was defined as when the average clearness index exceeded 0.6 from 1000 to 1400hh. Within an 8-day period, clear (cloudy) day mean $R_g$ and $\lambda E$ were calculated over 10hh to 14hh, and the ratio of cloudy to clear day values was calculated.
To overcome the cloud cover problem, we note that the ratio of cloudy to clear sky $R_g$ explains almost 70% of the variance in the ratio of cloudy to clear sky $\lambda E$ (Figure 6. 2 (b)), indicating that $\lambda E$ under cloudy conditions is mainly controlled by $R_g$ input, since the water vapor deficit is low and stomatal control is less significant (e.g. (Ryu et al. 2008a)). Thus, if $R_g$ under cloudy skies condition can be properly estimated, then $\lambda E$ under cloudy skies could be estimated using this relation. We propose that $R_g$ might be obtained in the following ways: First it can be directly estimated using MODIS data (Houborg et al. 2007; Ryu et al. 2008b). Second MODIS derived photosynthetically active radiation (PAR) (Liang et al. 2006) can be used as a surrogate for $R_g$ assuming that PAR is ~0.5 of $R_g$ (Jakovides et al. 2003). Lastly, $R_g$ can be derived from geostationary satellites (e.g. GOES) with higher (lower) temporal (spatial) resolution at low latitudes (Diak et al. 2004). If soil texture information is available, $\lambda E$ under cloudy skies can be directly estimated from GOES (Anderson et al. 2007).

Several uncertainties and caveats should be noted. First, if a whole 8-day period is cloudy, we do not recommend inferring $\lambda E$ from satellite-based sensors because of no valid data. Second, the upscaling factor, 0.370, may vary depending on locality. Under ideal conditions (e.g. no clouds with wet surface), it can be assumed that $\lambda E$ follows $R_g$ proportionally (Priestley and Taylor 1972). The potential scaling factor inferred from these ideal conditions is shown in Figure 6. 3. There is spatial and temporal variation of the scaling factor, but the ratio is quite conservative (0.3-0.45) up to 60 N in the growing season (Apr-Sep) (Figure 6. 3a). When averaging the quantities over the whole year, the ratio becomes more stable (0.34) up to 60 N, and quickly increase from 65 N (Figure 6. 3b). In high latitudes during summer, day length is very long and diurnal variation of $R_g$ is small due to Sun-Earth geometry (e.g. above the arctic circle, 66.6 N at summer solstice, there is sunlight 24 hours in a day). This potential ratio generally supports our result, but calls special attention for specific conditions such as higher latitude. Third, quality assurance flags or the MODIS Cloud Masking products should be used to identify bad quality data.
Figure 6.3. (a) Contour plot of the ratio of monthly mean \( S_e \) from 1000-1400hh to monthly mean 24-h \( S_e \) against months and northern latitudes. \( S_e \) is the extraterrestrial irradiance on a plane parallel to the Earth surface defined in Eq 6.2. (b) Yearly averaged ratio of monthly mean 24-h \( S_e \) for 24h (\( S_{all\ day} \)) to monthly mean \( S_e \) from 1000-1400hh (\( S_{mid\ day} \)).

6.4. Summary and Conclusions
Here we presented a temporal upscaling scheme from instantaneous (hourly) measurements near mid-day to 8-day mean values with an upscaling factor of 0.370 (95% CI 0.354, 0.385) based on 26 FLUXNET towers across 7 PFTs covering from boreal to tropical climatic zones. This approach works best with at least one $\lambda E$ estimate each day and we demonstrated a potential approach to infer $\lambda E$ in cloudy sky conditions. Our temporal upscaling scheme is applicable to MODIS and GOES, both of which revisit at least one time during the 1000-1400hh each day. We expect that this work will improve global estimates of $\lambda E$ across space and time.
References


Karlik, J.F., & McKay, A.H. (2002). Leaf area index, leaf mass density, and allometric relationships derived from harvest of blue oaks in a California oak savanna


Appendices

2. 1. Nomenclature

\( L_e \) effective leaf area index
\( L_t \) total plant area index that includes woody components
\( L \) leaf area index
\( W \) woody area index
\( B \) branch area index
\( T \) trunk area index
\( G \) projection coefficient of unit foliage area on a plane perpendicular to the view direction
\( \theta \) solar zenith angle
\( \theta_v \) view zenith angle
\( \theta_L \) leaf inclination angle - the angle between leaf normal and zenith
\( f(\theta_L) \) leaf inclination angle distribution function
\( P_o \) gap fraction
\( K \) contact number
\( \Omega \) clumping index
\( \Omega_E \) element clumping index
TRAC Tracing radiation and canopy architecture
DHP Digital hemispheric photography
DCP Digital cover photography (non-fisheye lens)
RTS Radiometer traversing system
CC clumping index calculated by Chen and Cihlar (1995)
LX clumping index calculated by Lang and Xiang (1986)
CLX clumping index that combines CC and CLX method suggested by Leblanc et al (2005)

2. 2. Distribution of tree numbers occurring on a circular subsample of given area

The distribution of tree numbers occurring on a circular subsample of given area was made using individual tree position within 200-m by 200-m LiDAR data. The mean canopy shape was applied to all individual trees to keep simplicity. Based on the program developed by Dr. Lang (personal communication with Dr. Lang), a circular subsample was randomly dropped on the 200-m by 200-m plot 10,000 times. At each time, the number of trees occurring on this subsample was calculated. The probabilities of occurring 0, 1, 2, 3, ... trees within the subsample was estimated and consequently, mean number, variance and relative variance (Fisher’s dispersion index, \( GI \) in Eq. 13) of the distribution was calculated. This process was repeated for subsample areas corresponding to the projection of mean tree crown on the horizontal surface at the \( \theta_v \) of 8, 22, 37, 52, 67, and 82° (Figure A1). Tree distribution is characterized as regular (\( GI<1 \)), random (\( GI=1 \)) and clumped (\( GI>1 \)). The result shows that \( GI \) were 0.83, 0.82, 0.83, 0.9, 1 and 1.6 for the \( \theta_v \) of 8, 22, 37, 52, 67, and 82°, respectively.
Figure A2. 1. The probabilities of the number of trees counted in the subsample areas corresponding to the projection of mean tree crown on the horizontal surface at the view zenith angles of 8, 22, 37, 52, 67, and 82.

2. 3. Influence of gaps between crowns on total gap fraction
Based on Nilson (1999) model simulation, we quantified gaps between crowns and total gaps. We compared the ratio of gaps between crowns to total gaps at the oak-savanna study site with three other species from sub-boreal region (Figure A2). Up to 68°, the proportion of between gaps to total gaps exceeded 50% at the oak-study site, which is higher than the other sites. The averaged ratio of between crown gaps to total gaps over the hemisphere (i.e. $\sin(\theta)$ weighted) was 60%.
Figure A2. 2. The ratio of gaps between crowns to total gaps among four tree species simulated by Nilson (1999) model. Canopy covers were 0.8, 0.9, 0.74 and 0.47 for birch, spruce, pine and blue oak, respectively. Data source of birch, spruce and pine is Nilson (1999).

5. 1. Description on the LED-spectrometer

In general, LEDs used as photo detectors produce a relatively high voltage (~1VDC) but this is not linear with intensity. In reverse mode they also produce a small current (micro-amps) that is linear with intensity of incident light. To measure this tiny current, an operational amplifier (op-amp LTC1050) is used as an inverting amplifier where \( V_{out} = -I_{in} \times R_f \). That is, the voltage out \( (V_{out}) \) equals the negative current in \( (\text{from the LED, } -I_{in}) \) times the feedback resistor \( (R_f) \). Two LEDs are wired in parallel to double the base current and connected in reverse polarity to the op-amp to correct the sign of the output voltage. While the LEDs and op-amps are relatively stable with temperature, care should be taken that the feedback resistor is also relatively stable with temperature. The op-amps require power and this is supplied with a DC/DC power converter that accepts a wide range of input voltages (9 to 36VDC) and outputs very stable 12VDC power. The voltage outputs from the op-amps are read by a Campbell data logger (CR23x) once every 10 seconds and recorded as 30 minute averages. The schematic of the LEDs derived NDVI instrument with a list of parts is illustrated in Figure A1.
5.2. Description of the sensor head

The upward sensor head is constructed from 1/4" (6.35 mm) and 3/8" (9.53 mm) rings cut from 2" (50.8 mm) OD aluminum pipe with 1/4" thick wall. These rings sandwich a circular plate 1/16" (1.59 mm) thick cut from round aluminum bar. The 1/4" ring is placed above the plate and the 3/8" ring below the plate. A 2" diameter disk of 1/32" (0.79 mm) thick Teflon sheet is placed on the top to diffuse the light and reduce the directional characteristics of the LEDs. Four LEDs (two red and two NIR) are mounted through the plate and affixed to the plate with a small circuit board using a central 6-32 screw. The whole assembly is bolted to a mounting arm using four 6-32 bolts running vertically though the Aluminum and Teflon parts at equal intervals around the diameter of the head. The downward sensor head is constructed similarly but oriented in the opposite direction. The outside is painted white to seal joints and reduce solar heating. Figure A2 shows the sensor head.
Figure A5. 2. LED-spectrometer head. The two red sensors are LEDs in the red wavelength, and the two colorless sensors are LEDs in the NIR wavelength. The white cover is Teflon to diffuse the incoming light.

5.3. Response of red and NIR LEDs to different solar zenith angles

To test the cosine response of LED-spectrometer equipped with Teflon diffuser, we compared the relative response of red and NIR LEDs (upward direction) with the ideal cosine curve (Figure A3). The difference between the LEDs and the ideal cosine curve was less than 20% within 60 degree of solar zenith angle and was ~ 30% at 70 degree of solar zenith angle.
Figure A5. 3. Relative response of the red and NIR LEDs compared with the ideal cosine curve. The data was taken in DOY207, 2007.
Figure A6.1. Scatterplot of 8-day, 24-h $\lambda E$ means against mid-day single-hourly means of $\lambda E$ for the corresponding 8-day periods for each PFT and hour around noon. The hourly average values are those of the specific hour over the 8-days, whereas the 8-day average values represent those of all hours of the day over the 8 days. The linear regressions were forced to pass the origin. Abbreviations of PFTs are the same as in Table A6.1.
Table A6. 1. Site information. CRO: crop, DBF: deciduous broadleaved forest, EBF: evergreen broadleaved forest, ENF: evergreen needle leaved forest. GRA: grassland, MF: mixed forest, WSA: woody savanna

<table>
<thead>
<tr>
<th>PFT</th>
<th>Site ID</th>
<th>Country and site name</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DE-Geb</td>
<td>Germany-Gebesee</td>
<td>(Anthoni et al. 2004)</td>
</tr>
<tr>
<td></td>
<td>JP-Mas</td>
<td>Japan- Mase paddy flux site</td>
<td>(Saito et al. 2005)</td>
</tr>
<tr>
<td></td>
<td>KR-Hnm</td>
<td>Korea-Haenam</td>
<td>(Ryu et al. 2008b)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DBF</td>
<td>CA-Oas</td>
<td>Canada-SSA old aspen</td>
<td>(Krishman et al. 2006)</td>
</tr>
<tr>
<td></td>
<td>DE-Hai</td>
<td>Germany- Hainich</td>
<td>(Kutsch et al. 2008)</td>
</tr>
<tr>
<td></td>
<td>US-MOz</td>
<td>US- Missouri Ozark Site</td>
<td>(Gu et al. 2007)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EBF</td>
<td>FR-Pue</td>
<td>France- Puechabon</td>
<td>(Allard et al. 2008)</td>
</tr>
<tr>
<td></td>
<td>IT-Cpz</td>
<td>Italy- Castelporziano</td>
<td>(Reichstein et al. 2007)</td>
</tr>
<tr>
<td></td>
<td>AU-Tum</td>
<td>Australia- Tumburumba</td>
<td>(Leuning et al. 2005)</td>
</tr>
<tr>
<td></td>
<td>ID-Pag</td>
<td>Indonesia- Palangkaraya</td>
<td>(Hirano et al. 2007)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ENF</td>
<td>FI-Hyy</td>
<td>Finland- Hyytiälä</td>
<td>(Suni et al. 2003)</td>
</tr>
<tr>
<td></td>
<td>NL-Loo</td>
<td>Netherlands-Loobos</td>
<td>(Dolman et al. 2002)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GRA</td>
<td>CH-Oe1</td>
<td>Switzerland- Oensingen1 grass</td>
<td>(Ammann et al. 2007)</td>
</tr>
<tr>
<td></td>
<td>NL-Ca1</td>
<td>Netherlands- Cabauw</td>
<td>(Jacobs et al. 2007b)</td>
</tr>
<tr>
<td></td>
<td>US-Var</td>
<td>US-Vaira ranch</td>
<td>(Xu and Baldocchi 2004)</td>
</tr>
<tr>
<td></td>
<td>CA-Var</td>
<td>Canada- Lethbridge</td>
<td>(Flanagan et al. 2002)</td>
</tr>
<tr>
<td></td>
<td>DE-Meh</td>
<td>Germany- Mehrstedt</td>
<td>(Scherer-Lorenzen et al. 2007)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MF</td>
<td>BE-Vie</td>
<td>Belgium- Vielsalm</td>
<td>(Aubinet et al. 2001)</td>
</tr>
<tr>
<td></td>
<td>CA-Gro</td>
<td>Canada- Groundhog River</td>
<td>(McCaughey et al. 2006)</td>
</tr>
<tr>
<td></td>
<td>CA-WP1</td>
<td>Canada-Western Peatland</td>
<td>(Syed et al. 2006)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WSA</td>
<td>US-SRM</td>
<td>US- Santa Rita Mesquite</td>
<td>(Scott et al. 2008)</td>
</tr>
<tr>
<td></td>
<td>AU-How</td>
<td>Australia- Howard Springs</td>
<td>(Beringer et al. 2007)</td>
</tr>
<tr>
<td></td>
<td>US-Ton</td>
<td>US-Tonzi ranch</td>
<td>(Baldocchi et al. 2004)</td>
</tr>
</tbody>
</table>