Use of High Resolution Lidar and Hyperspectral Data to Detect Changes in Energy Balance and Water Use Caused by Heterogeneity in Forest Structure.

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Introduction: Forest ecosystems modulate the climate through carbon sequestration but also through alterations of the surface roughness and the albedo which lead to changes in the energy and water balance. We test the use of variables derived from remotely sensed data as input into the Penman-Monteith (P-M) model to quantify these changes.

available energy *A*:

$$A = R_{net} - G \equiv 0.95 R_{net} = 0.95\left[\left(S\downarrow(1-\alpha)\right) + \left[(\varepsilon_a - \varepsilon_s)\sigma T_a^4\right]\right]$$

$$\varepsilon_a = 1 - 0.261 \exp\left[-7.77 \cdot 10^{-4}(273 - T_a)^2\right] \qquad \varepsilon_s \equiv 0.98$$

latent heat flux:

$$\lambda E = \frac{s\,A + \left(\rho c_p D_a / R_a\right)}{s + \gamma\left(1 + R_s / R_a\right)} \qquad \text{(P-M equation)}$$

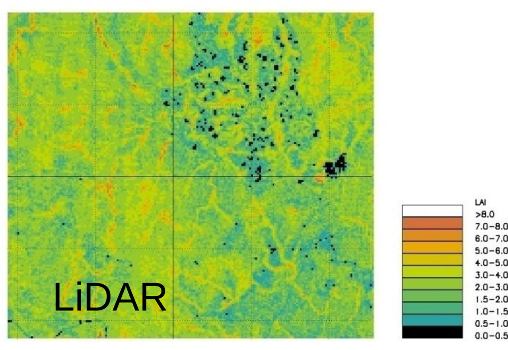
$$R_a = \frac{1}{k^2 U}\left[\ln\left(\frac{z-d}{z_0}\right)\ln\left(\frac{z-d}{z_{0H}}\right)\right] \qquad Rs = \frac{1}{c \cdot LAI}$$

Variables in blue indicate that they are measured at the tower, green stands for variables derived from remote sensing data.
R_{net} is net radiation, G the soil heat flux, $S\downarrow$ incoming shortwave radiation, α is albedo, ε_a is atmospheric emissivity and ε_s is surface emissivity, T_a is air temperature.
λE is the latent heat flux, s=de*/dT, the slope of the curve relating saturation water vapour pressure to temperature, γ is the psychrometric constant, $D_a=e^*(T_a)-e_a$ is the water vapour pressure deficit of the air, R_a is the aerodynamic resistance, R_s the surface resistance, z stands for height above ground , d for displacement height, z_0 and z_{0H} are the roughness length of momentum and sensible heat respectively. k is the von Karman constant (0.4) and U wind speed at reference height. *LAI* stands for leaf area index and c is the mean surface conductance per unit *LAI*.

leaf area index (*LAI*)

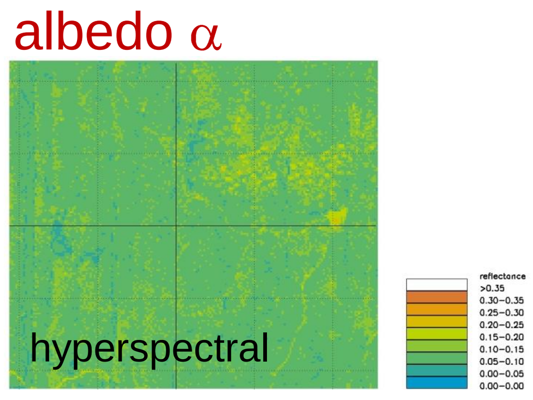
$$f_{cover(ul,ll)} = \frac{\sum P_{canopy(ul,ll)}}{\sum P_{all}} \quad + \quad$$

$\longrightarrow$

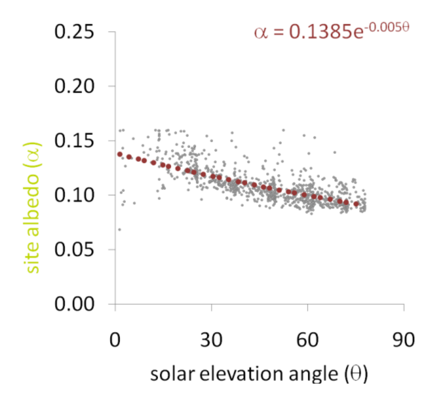


Calibration of LiDAR returns (f_{cover}) with digital hemispheric photography leads to LAI product [1,2]. *ul* and *ll* stand for upper and lower height limit (here 8 and 44 m).

albedo α



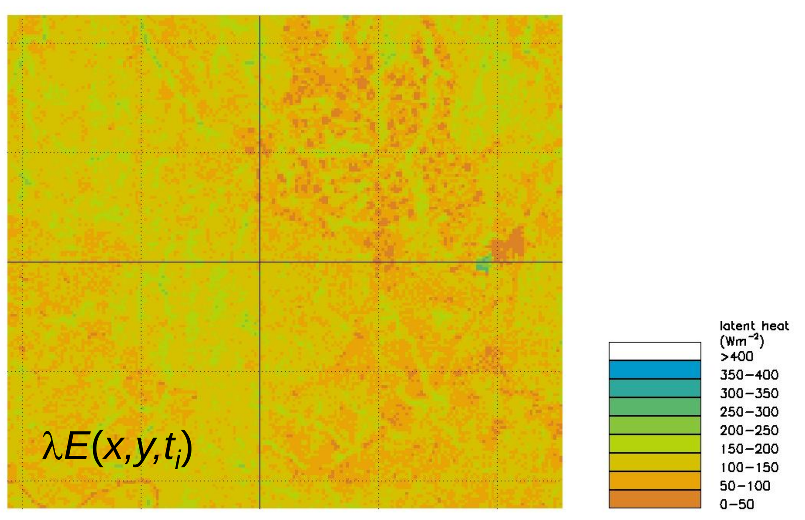
$+$

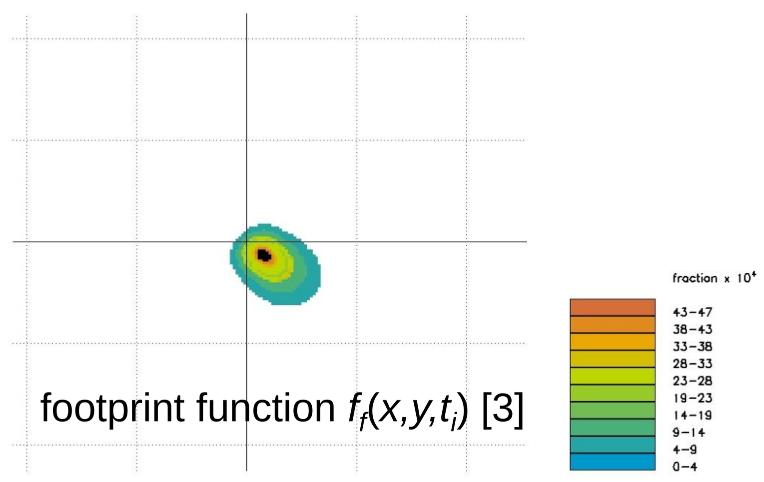


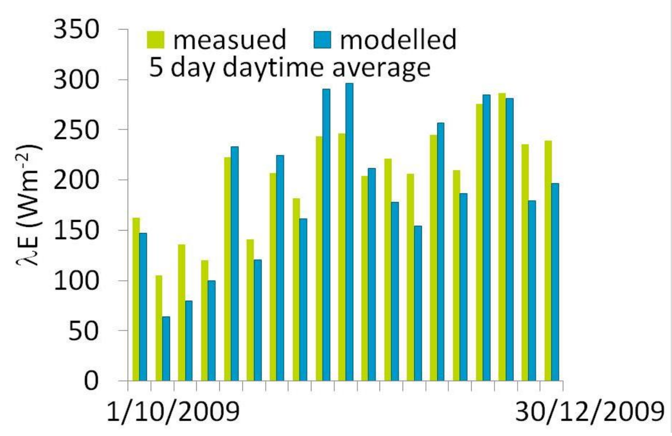
$\longrightarrow \quad \alpha(x,y,t)$

To create a time series of the spatial distribution of α the average α of the image is scaled to the site albedo as $f(\theta)$.

model validation and performance

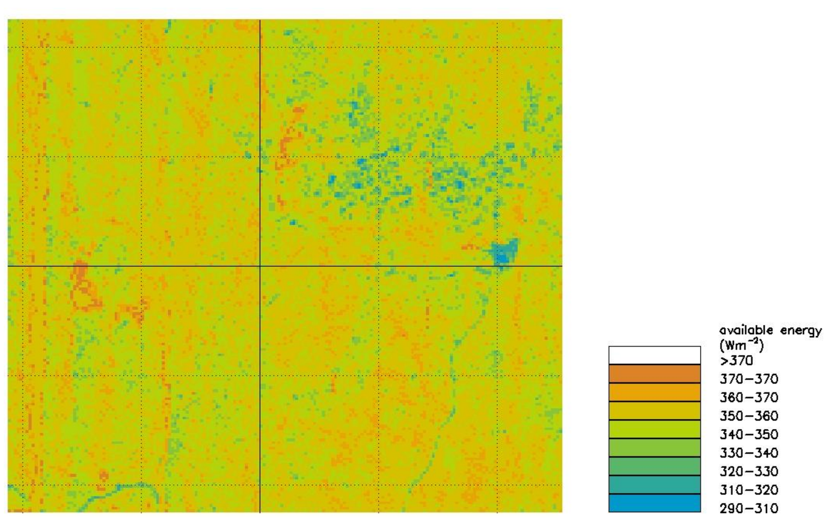


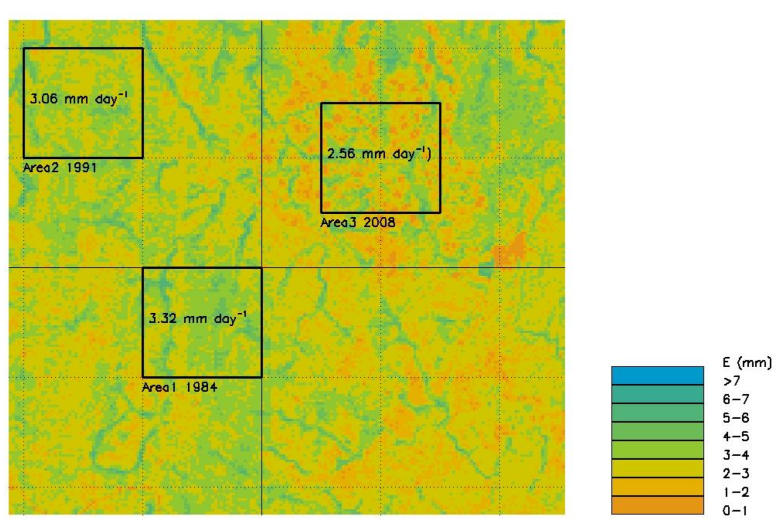


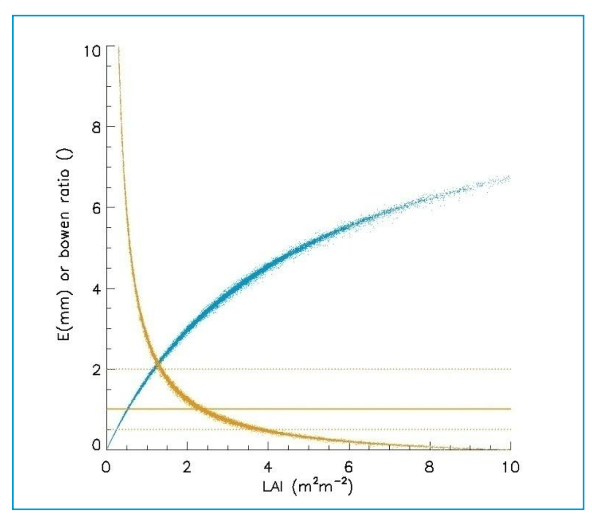


Hourly maps of λE are calculated. They are then footprint weighted and subsequently compared to λE measured at the tower (slope=1.00, r=0.73, fractional bias (fb)=0.04 and nmse=0.13). This is very similar to λE derived with an average *LAI* and *A* from the tower (slope = 1.18, r=0.75, fb=-0.14, nmse= 0.13). Aggregation of λE to 5 day daytime averages leads an improved correlation of r=0.88, indicating that heat storage should be accounted for at smaller time scales.
The equilibrium evapotranspiration for the time period is 1.58 times λE.

results







We can then investigate how inhomogeneities in forest structure caused e.g. by selective logging impact on the energy balance and water use. This is quantified for 3 example areas logged in 1984, 1991 and 2008 and confirms that less energy goes into evapotranspiration in the less recovered areas. Not only is less energy available in those areas (higher reflectance) but of that energy a relatively larger fraction goes into sensible heat (amber dots in scatter plot). Therefore the increase in water use is strongest for an increase in low LAIs (blue dots).

Conclusions

▪The P-M model provides a robust estimate of the latent heat flux derived from remote sensing[4] and - if optimised for c, the site specific mean surface conductance per unit *LAI* - allows the quantification of the impact of surface heterogeneity and disturbance on the energy balance and on the water use in high spatial resolution.

Outlook

▪Successful modeling of the albedo with a radiative transfer model will reduce the needed remote sensing data to lidar data.

▪Successful modeling of the heat storage will lead to an improved model performance on an hourly basis.

References *http://www.ozflux.org.au/monitoringsites/tumbarumba/index.html

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[4] Cleugh , H. et al. (2007): Regional evaporation estimates from flux tower and MODIS satellite data. Remote Sensing of Environment 106, 285-304.

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Further information

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