Spatial analysis of ground-based sun induced fluorescence data and canopy pigment content in a dry grassland

Szilvia Fóti[1,2], János Balogh[1], Alasdair Mac Arthur[3,4], Krisztina Pintér[1,2], Zoltán Nagy[1,2]

[1]*Institute of Biological Sciences, Szent István University, Páter K. u. 1, 2100 Gödöllő, Hungary*

[2]*MTA-SZIE Agroecology Research Group, Szent István University, 2100 Gödöllő, Hungary*

[3]*School of Geosciences, University of Edinburgh, Edinburgh EH9 3FF, UK; Alasdair.MacArthur@ed.ac.uk*

[4]*Laboratory for Earth Observation, Image Processing Laboratory, University of Valencia, Spain, Alasdair.MacArthur@uv.es*

[*]Corresponding author: foti.szilvia@mkk.szie.hu

Abstract

Monitoring of canopy photosynthetic performance in optimal and stress conditions has major importance in carbon budget estimates or in precision agriculture. Photosynthesis responds very rapidly to the environmental conditions balancing photochemical processes with different other processes through which excitation energy is lost from the system, including photo-protective heat loss and fluorescent light emission. Although the ratio of photosynthesis to fluorescence in optimal and stress conditions differ, it is not an easy task to assess their actual share, because of the quick adjustment of the pigment-protein complexes or the changing intensity of light re-absorption by chlorophylls.

Sun induced fluorescence (SIF) measured by ground-based instrument provided direct data of the photosynthetic capacity of the canopy. The O_2 absorptions bands filled with fluorescence served to calculate actual fluorescence intensity within the total upwelling signal. Furthermore, field leaf samples were collected and laboratory analysis was performed to determine photosynthetic pigment contents (both chlorophylls and carotenoids).

The sampling, both for SIF and pigment data collection followed spatial grid arrangements with different resolutions, 10 × 10 m and 30 × 30 m. Spatial analysis lays on a relatively large number of samples, collected within a very short time period. Our aim was to link the spatial distribution of one target phenomenon to the distribution or intensity of different driving forces, such as terrain features, soil moisture content, soil temperature etc., which data were also simultaneously collected during the field work. One measuring occasion at both spatial scales were selected for detailed spatial data processing with geostatistics and kriging.

Methods

Measured variables and sampling scheme

The measuring campaigns were very complex, consisting of several steps, including e.g.:

- GPS-based altitude (ALT) and position recording,
- sun induced fluorescence (SIF) measurement,
- RGB-photos to determine VIGreen (VI),
- leaf area index (LAI) measurement,
- canopy surface temperature measurements (Tsurf),

- biomass sampling (above ground biomass, AGB) for pigment content determination (chlorophyll a: Chl_a, b and carotenoids) and for plant water content determination,
- soil respiration (RS),
- soil temperature (TS) measurement at 5 cm depth,
- soil water content (SWC) measurement.

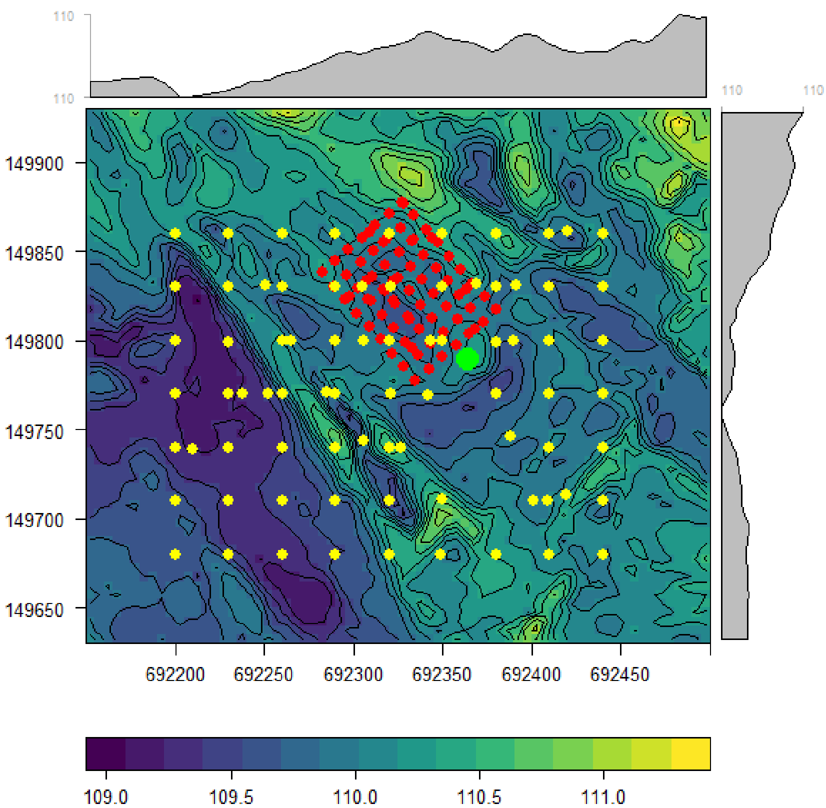

Figure 1: Two, different resolution grassland sampling grids (red spots: 10 m, yellow spots: 30 m) with the EC tower (green spot) pictured together with the 0.2 m resolution digital elevation model of the study site. Only 1.5 and 3 meters of altitudinal differences could be found at the smaller and larger resolution surveys, respectively.

The measurements followed the sampling grids (Figure 1.) for every variable, that is, at each measuring position, we took a series of measurements/samples/photos etc., then moved to the next position. The measuring campaigns were in this way very labour intensive, but a huge number of variables were gained, within the shortest time possible. The specificity of our measurements was that we used the instrument Piccolo Doppio in a ground-based mode, but not installed on a tower (providing point measurements). Instead, the instrument was mounted on a portable stand as an *in situ* instrument providing information related to the spatial pattern of SIF, as airborne and spaceborne methods do. Our analysis is at a preliminary stage, given that the SIF measurements started just in May 2019. Our SIF-derived metrics are also at a preliminary level focusing now on basic convolved values of fluorescence at the characteristic peaks in the apparent reflectance (at 687 nm in the O_2 B and 761 nm in the O_2 A bands, respectively).

Our ultimate task wihtin our project is to analyse the relationship between fine scale modeled spatial evapotranspiration (as a proxy for GPP) and ground measured canopy fluorescence. The relationship between ET and fluorescence (Figure 2.) is statistically significant even with the two to three days lags between the times of the SIF and ET records, repsectively. The scatter around this regression is large and may contain relevant information on the stress state of the vegetation.

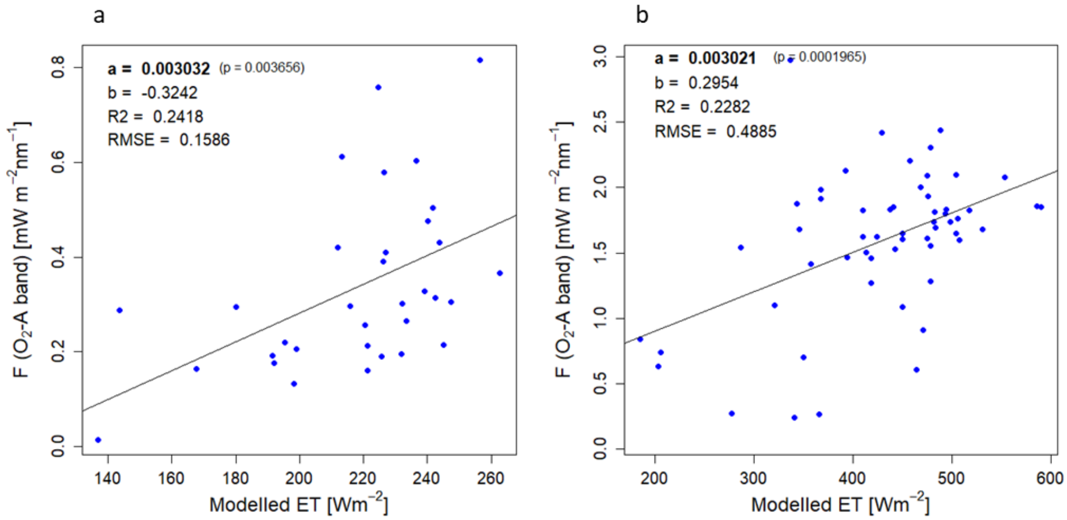

Figure 2: Relationship between fluorescence (O2-A band) from spatial measurements and modeled evapotranspiration (Modelled ET) at a species rich grassland (a) and a cropland (b). Spatial evapotranspiration values were extracted from ET maps by the pyTSEB software using thermal imagery acquired from an UAV within two days (not on the same day) to ground measurements of SIF by the Piccolo Doppio system. (The parameters of the fit are also presented: a: slope, p: significance value, b: intercept.)

Spatial data processing

The goal of the present study was to have an insight into the spatial intensity of some target variables (SIF-derived metrics, RS, VI, AGB and photosynthetic pigments) and into the spatial distribution of different driving forces (such as ALT, ALT-derived terrain features like topographic position index, TPI, SWC, TS, Tsurf). For this purpose, we conducted a detailed spatial data processing, including geostatistics and kriging. A few kriged maps with the underlying variograms will be presented in the following as our first results from our first measuring campaigns in May 22-23. (10 × 10 and 30 × 30 m grids, respectively) 2019, Bugac, Hungary, sandy grassland. This grassland is highly diverse both in surface characteristics and species composition.

Results

Patterns of driving variables on the 10 × 10 m grid

The driving variables followed ALT on the one hand (e.g., SWC, cf. Fig. 1.) and the ALT-derived TPI (e.g., Tsurf) on the other hand at the smaller grid.

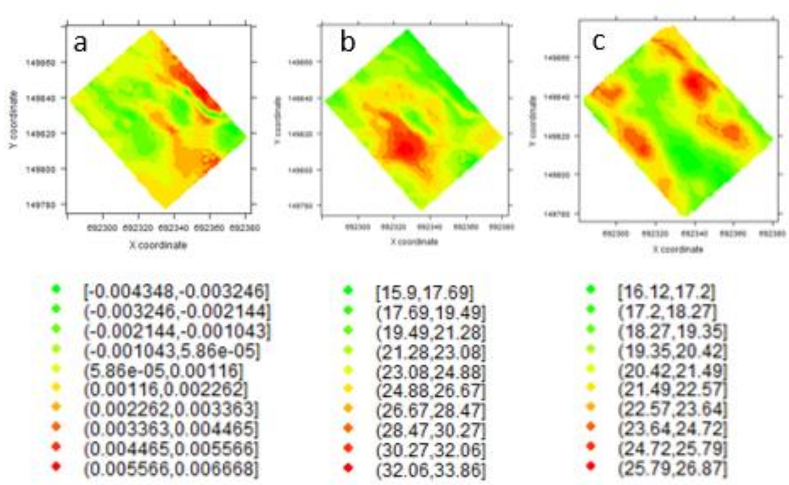

Figure 3.

Examples for the patterns of the driving variables at smaller extent and resolution in space, a: TPI, b: SWC, c: Tsurf.

Examples for variograms and maps of some target variables on the 10 × 10 m grid

Patterns of the target variables (Figure 4.), derived from SIF seemed to follow TPI and Tsurf more than SWC (cf. Fig. 3.), while patterns of the photosynthetic pigment content, vegetation greenness (VI) and soil respiration matched more the spatial distribution of the soil moisture.

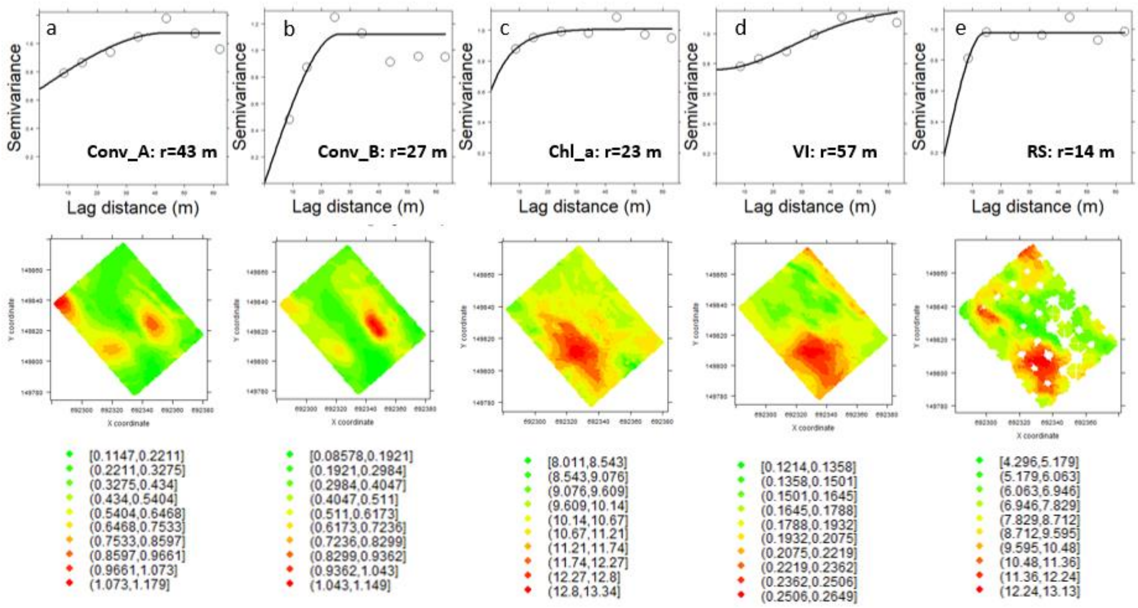

Figure 4: Variograms (upper row, r: range of autocorrelation) and kriged maps (lower row) for two SIF-metrics, convoluted value at the peaks of A (a: Conv_A) and B (b: Conv_B) bands, respectively, for chlorophyll a content (c: Chl_a), for VIgreen index (d: VI) and for soil respiration (e: RS - in this case, r is very close to the spatial resolution of the survey, which sometimes results in low interpolation capacity at some areas).

Examples for variograms and maps on the 30 × 30 m grid

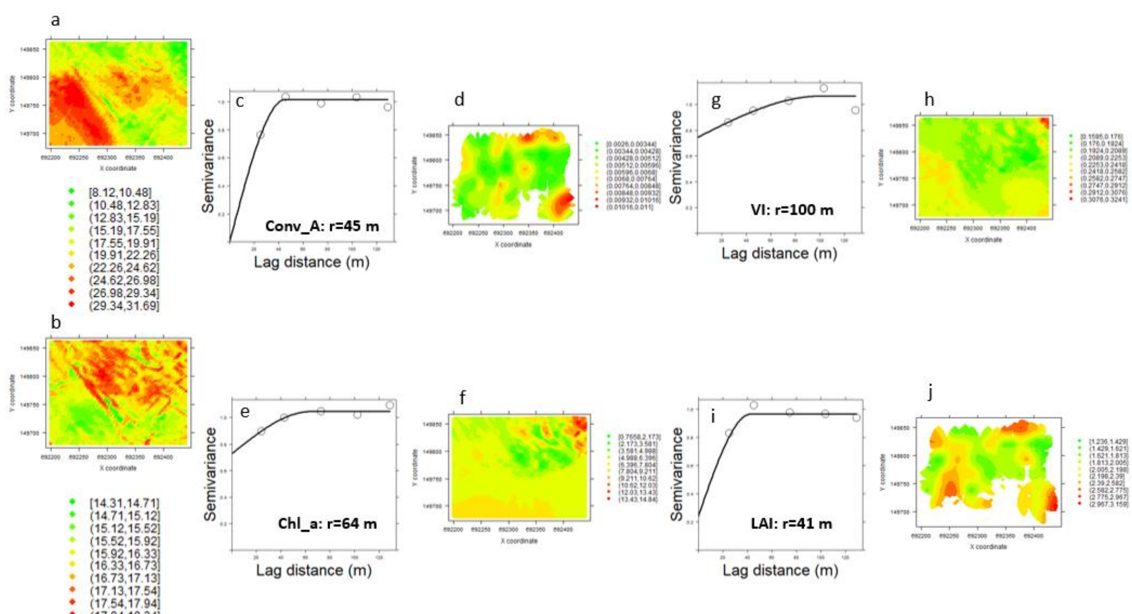

Figure 5: Some examples for kriged maps of background variables (a: SWC, b: Tsurf), SIF-derived metrics (c, d: variogram (r: range of autocorrelation) and map of the convoluted value at the peak of A), and other target variables, like photosynthetic pigment (e, f: variogram and map of chlorophyll a), VIgreen index (g, h: variogram and map of VI) and leaf area index (I, j: variogram and map of LAI) at the 30 × 30 m sampling grid from Bugac. Here as well (d and j maps), r is very close to the spatial resolution of the survey, which sometimes results in low interpolation capacity at some areas.

A slightly less correlation could be observed at the larger spatial extent and resolution survey (Figure 5.), but SWC and Tsurf seemed to correlate negatively which is a general observation for spatial datasets (at least, SWC- TS correlation is negative in general through higher evaporative cooling of larger SWC), while Chl_a, VI, LAI and Conv_A seemed to show similarities in their spatial intensities. However, we need to include more, already collected datasets in our further, more detailed analysis to be able to reveal those correlations, on the basis e.g., of cross-variogram analysis.