Agricultural and Forest Meteorology 260–261 (2018) 144–153

Contents lists available at ScienceDirect

Agricultural and Forest Meteorology

journal homepage: www.elsevier.com/locate/agrformet

Contributions of landscape heterogeneity within the footprint of eddy-covariance towers to flux measurements

Vincenzo Giannico[a,b], Jiquan Chen[b,*], Changliang Shao[c], Zutao Ouyang[b], Ranjeet John[b], Raffaele Lafortezza[d,a]

[a] Department of Agricultural and Environmental Sciences, University of Bari "A. Moro", Via Amendola 165/A 70126, Bari, Italy
[b] Center for Global Change and Earth Observations (CGCEO), Michigan State University, East Lansing, MI 48823, USA
[c] National Hulunber Grassland Ecosystem Observation and Research Station & Institute of Agricultural Resources and Regional Planning, Chinese Academy of Agricultural Sciences, Beijing 100081, China
[d] Department of Geography University of Hong Kong Centennial Campus, Pokfulam Road Hong Kong

ARTICLE INFO

Keywords:
Eddy covariance
Landscape heterogeneity
Footprint
Bayesian
Mongolia

ABSTRACT

Flux measurements based on aerodynamic principles (e.g., eddy covariance method, or EC) assume the vegetation and landform within the footprint must be flat, large, and homogeneous, although very rarely do flux tower sites meet such requirements. Here, using two long term EC tower sites in Mongolian grasslands, we test a hypothesis that the magnitude and variation of EC flux measurements are partially dependent of landscape heterogeneity. We define landscape heterogeneity as the spatial composition and distribution of components within the footprint of a flux tower, which was quantified using high resolution WorldView-2 images to extract vegetation texture features (*Contrast*, *Dissimilarity* and *Entropy*). Bayesian analysis was performed to model the linkage of landscape heterogeneity with EC fluxes of CO_2 in 8 intercardinal directions by dissecting it into 5 distances. We found that higher levels of landscape heterogeneity have an impact on flux measurements, especially under stable conditions. Specifically, a total of 24 Bayesian models based on the EVI-derived texture features passed the Gelman and Rubin convergence diagnostic statistic test. A positive relationship is shown between the percentage of footprint cover ($Footprint\%_{sector}$) and landscape texture features (*Contrast* and *Dissimilarity*), with the footprint cover acting as a function of heterogeneity under stable conditions. Negative effects were found when modeling CO_2 flux (Fc_{sector}) with *Contrast* under stable and unstable conditions, and with *Dissimilarity* and *Entropy* under stable conditions. With increases in high resolution remote sensing images and UAV technology (e.g., LiDAR), the results and approaches outlined in this study highlight new frontiers and opportunities for the FLUXNET community to integrate flux measurements and high-resolution remote sensing data, promoting a new generation of footprint models, and exploring the cohesive connections between flux measurements and the underlying processes (e.g., soil, physiological, ecosystem processes).

1. Introduction

A fundamental assumption in flux measurements based on aerodynamic principles, including the eddy-covariance (EC) method, Bowen ratio method, and others, is that the vegetation and land form surrounding a tower is flat, large, and homogenous (Lee et al., 2006). This assumption is necessary for ensuring that the contributions from horizontal and vertical advections are minimized for accurate calculations of the vertical fluxes (e.g., the net exchange between the atmosphere and the vegetation). Otherwise, the non-zero mean advection induced by convergence or divergence of flow due to spatial source/sink in homogeneity needs to be corrected (Lee, 1998; Paw et al., 2000; Massman and Lee, 2002). Given these requirements, all parcels within the footprint of a flux tower will have the potential to contribute equally to the quantities measured at the sensor location so that the ecosystem-level fluxes are accurately represented. This assumption is conventionally met through site selection when installing a tower. Unfortunately, such an ideal site rarely exists across global terrestrial surfaces. We speculate that many tower sites within the FLUXNET community may not meet these requirements. Few scientific reports in the literature have attempted to assess the heterogeneity of flux towers using high resolution satellite images, nor has an effort been made to quantify the contributions of vegetation mosaics within the footprint to the vertical fluxes of materials (Xu et al., 2017).

* Corresponding author.
E-mail address: jqchen@msu.edu (J. Chen).

https://doi.org/10.1016/j.agrformet.2018.06.004
Received 29 January 2018; Received in revised form 21 May 2018; Accepted 5 June 2018

Numerous efforts, however, have been made to correct the *in situ* flux measurements to overcome the conversion/diversion processes caused by complex terrains (Froelich and Schmid, 2002; Lee and Hu, 2002; Davis et al., 2003). The dominant approach has been based on rotating the mainstream fluxes to reflect the vertical fluxes, including the widely recognized methods of 2D, 3D, or planetary rotation (Goulden et al., 1996; Twine et al., 2000). This is achieved by advancing the classical footprint model (Schmid, 2002) to examine the deviations from the horizontal plain (Kormann and Meixner, 2001; Kljun et al., 2002; Froelich and Schmid, 2002). These corrections have improved our estimates taken on slopes and in areas with directional air movement (e.g., cold drainage). However, no study has considered the error terms caused by vegetation heterogeneity (i.e., spatial variation in vegetation composition and structure), likely due to the lack of high-resolution data on the vegetation and landform within the footprint of a tower. With the availability of high-resolution data from recent satellites or UAV, it is now possible to integrate the footprint models and flux measurements with heterogeneity metrics. More importantly, connecting the vegetation heterogeneity with tower-based fluxes will provide us with a more direct and powerful avenue to explore the role of vegetation in regulating ecosystem fluxes.

In this study, we define landscape heterogeneity as the spatial composition and distribution of landscape components within the footprint landscape (Forman, 1995). Such heterogeneity is often explained in terms of landscape features calculated from images using Haralick texture features (Haralick et al., 1973; Kayitakire et al., 2006; Ozdemir and Karnieli, 2011). For example, it is possible to calculate texture features related to the differences among neighborhood pixels (i.e., *Contrast* and *Dissimilarity*) and to the level of orderliness among pixel values (*Entropy*).

The primary objective of this study is to test a hypothesis that the magnitude and variation of EC flux measurements are partially dependent of landscape heterogeneity as defined above. In particular, we aim to answer the following questions: (i) Is the variation in EC fluxes (e.g., CO_2) partially dependent on landscape heterogeneity? (ii) If that dependency exists, are there distinctions among different texture features? And (iii) What are the differences between estimates under stable and unstable conditions? To answer these questions, we investigated the empirical relationships between texture features derived from high-resolution data at two EC flux towers in Mongolia where the surrounding landforms were flat and the vegetation was seemingly homogeneous for at least 1 km (Shao et al., 2017). CO_2 flux (Fc) was partitioned over space using a footprint model and normalized over wind direction by employing a clustering algorithm. The results and models developed through this study can be used to support decisions in evaluating new and established EC flux tower sites and understanding how within-ecosystem variation of vegetation/soil may influence ecosystem fluxes. Additionally, this study sets a pioneer step in design future footprint models that integrate landscape heterogeneity and EC fluxes for the FLUXNET community.

2. Materials and methods

2.1. Study area

The two flux towers considered in our study are located in the west of Ulaanbaatar, the capital city of Mongolia (Fig. 1). The region is characterized by a continental climate; the annual mean air temperature is 1.2 °C; the mean precipitation is 196 mm that follows an irregular seasonal pattern. The first flux tower is dominated by *Leymus chinensis* and is classified as a meadow steppe (MDW) with permafrost substratum. The second site is classified as a short-grass typical steppe (TPL) and is dominated by *Stipa krylovii* and *Artemisia frigida* (Shao et al., 2017). The area around each flux tower was divided into eight secondary-intercardinal directions, labeled as: North North-East (NNE), North-East East (NEE), East South-East (ESE), South-East South (SES), South South-West (SSW), South-West West (SWW), West North-West (WNW), North-West North (NWN) (Fig. 2). Each section was successively divided into 5 sectors by distance from the tower (i.e., 50 m, 100 m, 200 m, 500 m, 1 km), yielding a total of 40 sectors around each EC tower.

2.2. High-resolution vegetation distribution

We searched the available, high resolution imagery for our study sites during 2014–2015 and found one WorldView-2 image on June 6, 2013 as the closest one by date for the study period to describe the vegetation heterogeneity within the footprint of the tower. This image consists of eight color bands (red, green, blue, coastal, yellow, red edge, and two near-infrared bands) at 1.84 m spatial resolution and one panchromatic band at 0.46 m spatial resolution. The image was provided by the National Geospatial-Intelligence Agency (NGA), commercial Archive Data (https://cad4nasa.gsfc.nasa.gov/).

After preprocessing the image, we extracted various texture features (*Contrast*, *Dissimilarity* and *Entropy*). In brief, the ENVI 5.1 tool (Exelis Visual Information Solutions, Boulder, Colorado) was employed to radiometrically and atmospherically correct the image after the orthorectification procedure. We extracted two vegetation indices (VIs) from the image: the enhanced vegetation index (EVI) and the normalized difference vegetation index (NDVI). Both VIs were used to calculate texture features using the Gray-Level Co-occurrence Matrices (GLCMs)-based filter implemented in ENVI. GLCM is a matrix that summarizes the relative frequency of how often two different quantized pixel values occur in a specified spatial relationship (Haralick et al., 1973). The GLCM is calculated after quantizing the VIs into 64-integer values with a window of 3 × 3 pixels. The window size was set on the basis of a previously conducted correlation test. The GLCM was therefore used to calculate the different texture features.

Texture features can be broadly divided into edge and interior features (Hall-Beyer, 2017). Edge features, including *Contrast*, *Dissimilarity* and *Entropy*, are likely to have greater values in areas with large differences between neighborhood pixels. Areas with these features that yield high values typically represent heterogeneous areas and natural or artificial edges. *Contrast* and *Dissimilarity* have similar behaviors and are more likely to increase where linear edges are evident although *Dissimilarity* increases linearly while *Contrast* increases exponentially. On the other hand, *Entropy* is expected to be higher where the pattern of heterogeneity is irregular and the edges are not continuous with such complex system edges (i.e., forest-wetland boundaries).

On the contrary, interior features (e.g., *Homogeneity*, *Correlation* or *Mean*) have a positive relationship with homogeneity and can yield high values in areas where the pixels have very similar values to their neighboring pixels. In this study, we focused on texture features describing landscape heterogeneity (*Contrast*, *Dissimilarity* and *Entropy*) that are calculated as the following:

$$Contrast = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} (i-j)^2 P(i, j) \tag{1}$$

$$Dissimilarity = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} |i-j| \, P(i, j) \tag{2}$$

$$Entropy = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} P(i, j) \log(P(i, j))) \tag{3}$$

where $P(i,j)$ represents the normalized value of the GLCM at (i,j) and N_g represents the number of quantified values of the image. All texture measures were averaged by sector (Fig. 3). Frequently, texture features are correlated with each other. Such correlation may depend on various factors such as the image's spatial resolution or the ecosystem analyzed. Therefore we selected only those features that were not significantly