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# Assessing the representativeness of the AmeriFlux network using MODIS and GOES data

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[1] The AmeriFlux network of eddy covariance towers has played a critical role in the analysis of terrestrial water and carbon dynamics. It has been used to understand the general principles of ecosystem behaviors and to scale up those principles from sites to regions. To support the generalization from individual sites to large regions, it is essential that all major ecoregions in North America are represented in the AmeriFlux network. In this study, we examined the representativeness of the AmeriFlux network by comparing the climate and vegetation across the coterminous United States in 2004 with those at the AmeriFlux network in 2000–2004 on the basis of remote sensing products. We found that the AmeriFlux network generally captured the climatic and vegetation characteristics in the coterminous United States with under-representations in the Rocky Mountain evergreen needleleaf forest, the Sierra Nevada Mountains, the Sonora desert, the northern Great Plains, the Great Basin Desert, and New England. In terms of site representativeness, our analysis suggested that Indiana Morgan Monroe State Forest, Indiana, and Harvard Forest, Massachusetts, were among the forest sites with high representativeness extents; while Audubon Research Ranch, Arizona, and Sky Oaks Young Chaparral were among the nonforest sites with high representativeness extents.

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## 1. Introduction

[2] The AmeriFlux network of eddy covariance towers was established in 1996 to quantify the spatial and temporal variations of water and carbon exchanges between terrestrial ecosystems and the atmosphere, and to understand the underlying processes regulating the interannual variations of water and carbon fluxes at different scales [*Hargrove et al.*, 2003]. The network also serves as the backbone for the North American Carbon Program (NACP) to measure and understand the sources and sinks of carbon dioxide ($CO_2$), methane ($CH_4$) and carbon monoxide (CO) in North America [*Hargrove et al.*, 2003; S. C. Wofsy and R. C. Harriss, 2002, North America carbon program (NACP): A report of the NACP Committee of the U.S. carbon cycle science steering group, available at http://www.carboncyclescience.gov/default.php]. By 2005, the AmeriFlux network included more than 120 independently funded sites operating across North, Central and South America (B. E. Law et al., 2005, AmeriFlux Strategic Plan, Oak Ridge National Laboratory, Oak Ridge, Tennessee, available at http://public.ornl.gov/ameriflux/about-strategic_plan.shtml).

[3] Measurements from the AmeriFlux network have been used to investigate the seasonal and interannual patterns of vegetation photosynthesis and respiration processes [*Falge et al.*, 2002], the influence of vegetation phenology on net carbon uptake [*White and Nemani*, 2003], the impact of disturbance on carbon balances [*Saleska et al.*, 2003], and the relationships between climate, energy, water, and carbon dynamics [*Baldocchi et al.*, 2001]. However, most of these studies are site-specific. Studies on water and carbon dynamics from the AmeriFlux network over large areas are only made possible with increasing flux observations in recent years coupled with empirical modeling techniques using remotely sensed data. For example, *Wylie et al.* [2003] related coarse resolution normalized difference vegetation index (NDVI) to 14-day average daytime $CO_2$ fluxes in a sage-brush-steppe ecosystem. *Rahman et al.* [2005] observed a strong correlation of 0.77 between tower-based gross primary production (GPP) and enhanced vegetation index (EVI). *Nagler et al.* [2005] developed an empirical relationship for evapotranspiration (ET) predictions over large reaches of western U.S. rivers by combining remote sensing with flux observations. These studies established the potential of extrapolating knowledge

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learned at AmeriFlux sites to large regions (Law et al., 2005). More recently, *Yang et al.* [2006, 2007] had used an inductive machine learning technique for the development of predictive ET and GPP models from the AmeriFlux network and applied the models to the coterminous United States with results comparable to other existing ET and GPP models [*Nishida et al.*, 2003; S. W. Running et al., 1999, MODIS daily photosynthesis (PSN) and annual net primary production (NPP) product (MOD17), algorithm theoretical basis documents, available at http://www.ntsg.umt.edu/modis/ATBD/ATBD_MOD17_v21.pdf].

[4] To support the generalization from individual sites to large regions and to understand the behaviors of water and carbon variations across North America, it is essential that major ecoregions from North America are represented in the AmeriFlux network [*Hargrove et al.*, 2003]. Fortunately, a study conducted by *Hargrove et al.* [2003] has already shown that the distributions of AmeriFlux sites are generally representative for the coterminous United States. The results were based on a cluster analysis with 59 AmeriFlux sites using 25 climatic and physiographic forcings including elevation, mean and extremes of annual temperature, mean monthly precipitation, soil nitrogen, organic matter, water capacity, frost-free days, soil bulk density and depth, solar aspect and insolation. *Hargrove et al.* [2003] found that the vast continental interior was well-represented by the AmeriFlux network but that the Pacific Northwest, the Sierra Nevada Mountains, the Sonora desert, and Texas grassland/croplands were under-represented.

[5] Assessing the representativeness of the AmeriFlux network is a challenging task that should benefit from multiple approaches staged throughout the life of the network. We suggest that the representativeness of the AmeriFlux network will be more convincing if independent studies come to similar conclusions. Hence, the goal of our research is to provide an independent study for the AmeriFlux representativeness analysis. More specifically, instead of using a broad spectrum of topographic, soil, and climate variables [*Hargrove et al.*, 2003], we focused our representativeness analysis on remotely sensed climate and vegetation products. Such an analysis can serve as a complement to previous work [*Hargrove et al.*, 2003]. In the following sections, we present (1) a brief description on AmeriFlux sites; (2) a description on data and methods used; and (3) results of our representativeness analysis.

## 2. Sites

[6] Our analysis included all active AmeriFlux sites in 2000–2004 over the coterminous United States with data compiled and published by Oak Ridge National Laboratory (ORNL) (Table 1 and Figure 1). These sites represent a wide diversity of climate and vegetation structures: climatic conditions range from temperate, tropical, to arid regions; vegetation varies from boreal to evergreen forests, deciduous forests, grassland, shrublands, and agricultural croplands (Law et al., 2005).

[7] AmeriFlux sites report hourly or half-hourly measurements of biosphere-atmosphere carbon, water and energy fluxes, and meteorological observations with additional information on vegetation structures and soil characteristics. By 2005, the average running length was 2.5 years with approximately 20% of the sites having 5–10 years of records (Law et al., 2005).

[8] Flux footprint is an important concept in the AmeriFlux network and is defined over an upwind area of the measurement site contributing to the flux measured. It varies with atmospheric stability and surface roughness [*Horst and Weil*, 1994]. A concept closely related to footprint is fetch, which is defined as the extent of a relatively uniform area upwind. A rule of thumb suggests a ratio of 100:1 between fetch and tower height [*Moncrieff et al.*, 1997]. However, studies [*Horst and Weil*, 1994] have found that the fetch-height ratio can be considerably greater than 100:1 under stable conditions with heterogeneous vegetation and rough terrains. The tower height of AmeriFlux sites varies from 2 m (Varia Ranch, California) to 73 m (Wind River, Washington) with the exception of Park Fall, Wisconsin, which has a height of 447 m (Table 1). Generally, because of high surface heterogeneity, forest sites have tower heights greater than 20 m, and consequently represent a fetch greater than 2 km.

## 3. Data and Methods

### 3.1. Remote Sensing Variable Selection

[9] Decades of ecosystem modeling efforts have identified that the most critical environmental driving variables for ecosystem studies are incident shortwave radiation (SWR), land surface temperature (LST), humidity, precipitation, and wind [*Waring and Running*, 1998]. Weather station networks have long been the primary data source for these variables. A common practice is to acquire meteorological data from weather station networks and then extrapolate the data across the landscape.

[10] Since the early 1970s, satellite remote sensing has been widely used for ecological studies. Remote sensing has the advantage of broad spatial coverage and regular temporal sampling. Therefore, models based on or ingesting remote sensing data are theoretically capable of accurately predicting critical ecological variables such as water and carbon fluxes at large regions.

[11] SWR and LST are among the most critical environmental driving variables for ecosystem studies currently available from remote sensing. Although humidity and precipitation are preferred if available, they are closely related to LST [*Hashimoto et al.*, 2008]. On the other hand, wind is too variable to be predicted from satellite remote sensing or geostatistical methods. Therefore, a constant wind speed is often assumed in many ecosystem analyses [*Waring and Running*, 1998]. On the basis of these considerations and data availability, we selected SWR and LST as the climatic variables for our representativeness analysis.

[12] Vegetation physiological properties are also important factors that must be considered in ecological analysis. However, it is inevitable that stand-level details (e.g., the characteristics of individual trees or species) have to give way to general physiological properties (e.g., vegetation index) to facilitate ecosystem studies over large regions. Two important vegetation products available from remote sensing are leaf area index (LAI) and vegetation indices (VIs). Because many studies [e.g., *Wylie et al.*, 2003; *Yang et al.*, 2006, 2007] have shown that VIs are a good indicator for predictions of water and carbon fluxes over large

**Table 1.** Name, Latitude, Longitude, Vegetation Structure, and Years of Data Available for Each Flux Site in This Study

| Name | Latitude (°) | Longitude (°) | Vegetation Structure | Tower Height (m) | Year |
|---|---|---|---|---|---|
| | | *Forest* | | | |
| Indiana Morgan Monroe State Forest (MMSF), Indiana | 39.3232 | −86.4134 | deciduous broadleaf forest | 48.0 | 2000–2002 |
| Blodgett, California | 38.8953 | −120.6328 | evergreen needleleaf forest | 12.5 | 2000–2004 |
| University of Michigan, Michigan | 45.5598 | −84.7138 | mixed forest | 50.0 | 2000–2003 |
| Niwot Ridge Forest, Colorado | 40.0329 | −105.5464 | evergreen needleleaf forest | 26.0 | 2000–2004 |
| Howland Forest Main, Maine | 45.2041 | −68.7403 | mixed forest | 29.0 | 2000–2004 |
| Howland Forest West, Maine | 45.2091 | −68.7470 | mixed forest | n/a | 2000–2004 |
| Howland Forest Harvest, Maine | 45.2072 | −68.7250 | mixed forest | n/a | 2003–2005 |
| Harvard Forest, Massachusetts | 42.5378 | −72.1715 | deciduous broadleaf forest | 30.0 | 2000–2004 |
| Willow Creek, Wisconsin | 45.9059 | −90.0799 | mixed forest | 30.0 | 2000–2004 |
| Park Falls, Wisconsin | 45.9459 | −90.2723 | mixed forest | 447.0 | 2000–2004 |
| Metolius Intermediate, Oregon | 44.4524 | −121.5572 | evergreen needleleaf forest | 31.0 | 2002–2004 |
| Metolius Old Young, Oregon | 44.4372 | −121.5668 | evergreen needleleaf forest | n/a | 2000–2002 |
| Metolius Old, Oregon | 44.4992 | −121.6224 | evergreen needleleaf forest | 47.0 | 2000–2000 |
| Sylvania Wilderness Area, Michigan | 46.2420 | −89.3477 | mixed forest | 37.0 | 2001–2004 |
| Duke Forest Pine, North Carolina | 35.9782 | −79.0942 | mixed forest | 20.6 | 2000–2003 |
| Dukeforest Hardwood, North Carolina | 35.9736 | −79.1004 | mixed forest | 42.0 | 2000–2004 |
| Black Hills, South Dakota | 44.1580 | −103.6500 | evergreen needleleaf forest | 24.0 | 2001–2004 |
| Donaldson, Florida | 29.7548 | −82.1633 | evergreen needleleaf forest | 15.0 | 2000–2002 |
| Austin Cary, Florida | 29.7381 | −82.2188 | evergreen needleleaf forest | 30.0 | 2000–2004 |
| Kennedy Space Center (KSC) Scrub Oak, Florida | 28.6086 | −80.6715 | evergreen broadleaf forest | 18.0 | 2000–2003 |
| Kennedy Space Center (KSC) Slash Pine, Florida | 28.4583 | −80.6709 | evergreen broadleaf forest | n/a | 2002–2002 |
| Mize, Florida | 29.7648 | −82.2448 | evergreen needleleaf forest | 7.0 | 2000–2003 |
| Wind River, Washington | 45.8205 | −121.9519 | evergreen needleleaf forest | 73.0 | 2004–2004 |
| Walker Branch, Tennessee | 35.9588 | −84.2874 | deciduous broadleaf forest | 44.0 | 2002–2004 |
| Ozark, Missouri | 38.7441 | −92.2001 | deciduous broadleaf forest | 30.0 | 2004–2004 |
| | | *Nonforest* | | | |
| Walnut River, Kansas | 37.5208 | −96.8550 | grassland | 2.1 | 2001–2004 |
| Duke Forest Openfield, North Carolina | 35.9712 | −79.0934 | grassland | 2.8 | 2001–2004 |
| Lost Creek, Wisconsin | 46.0827 | −89.9792 | shrubland (deciduous wetland) | 10.2 | 2000–2004 |
| Bondville, Illinois | 40.0061 | −88.2919 | cropland | 10.0 | 2000–2004 |
| Mead Rainfed, Nebraska | 41.1797 | −96.4396 | cropland | 6.0 | 2001–2004 |
| Mead Irrigated, Nebraska | 41.1651 | −96.4766 | cropland | 6.0 | 2001–2004 |
| Mead Rotation, Nebraska | 41.1649 | −96.4701 | cropland | 6.0 | 2001–2004 |
| Vaira Ranch, California | 38.4067 | −120.9507 | grassland | 2.0 | 2000–2004 |
| Tonzi Ranch, California | 38.4316 | −120.9660 | shrubland/savanna | 23.0 | 2001–2004 |
| Fort Peck, Montana | 48.3079 | −105.1005 | grassland | 3.5 | 2000–2004 |
| Sky Oaks Old Chaparral, California | 33.3739 | −116.6230 | shrubland/savanna | 4.5 | 2000–2004 |
| Sky Oaks Young Chaparral, California | 33.3772 | −116.6230 | shrubland/savanna | 2.5 | 2000–2004 |
| Canaan Valley, West Virginia | 39.0633 | −79.4208 | grassland | 4.0 | 2004–2004 |
| Goodwin Creek, Mississippi | 34.2500 | −89.9700 | grassland | 4.0 | 2002–2004 |
| Audubon Research Ranch, Arizona | 31.6000 | −110.5104 | grassland | 4.0 | 2002–2004 |
| ARM Oklahoma, Oklahoma | 36.6050 | −97.4850 | cropland | 60.0 | 2003–2004 |

regions, we selected VIs as the vegetation characteristic for our representativeness analysis. In addition, we also included land cover in our analysis so as to further differentiate different vegetation types. In summary, we selected LST, SWR, VI and land cover as the basis of our representativeness analysis of the AmeriFlux network.

## 3.2. Data

### 3.2.1. Data Sources and Considerations of Spatial and Temporal Resolutions

[13] We examined two types of data: (1) meteorological data (LST and SWR); and (2) vegetation data (VI and land cover); among which LST and VI came from the standard Moderate Resolution Imaging Spectroradiometer (MODIS) products, land cover came from ground observations and MODIS, and SWR came from the Surface Radiation Budget project (SRB) derived from the Geostationary Operational Environmental Satellite (GOES) [*Pinker et al.*, 2002]. We used MODIS products due to its moderate spatial resolution (250 m ~ 1 km), high temporal resolution (daily ~ 16-day) and free accessibility, making it ideal for regional ecosystem studies [*Lillesand et al.*, 2003]. MODIS provides two vegetation indexes, NDVI and EVI. EVI has been designed to be robust to background noise and remain sensitive to high biomass regions (e.g., forests) [*Huete et al.*, 2002]; hence we selected EVI as the vegetation index. Currently, GOES-SRB SWR is the only remotely sensed radiation data set routinely available at continental to global scales.

[14] Conceptually, we used a temporal and spatial analysis design to match both data availability (section 3.2.2) and generally the flux tower footprint (section 2). Temporally, we chose 2000–2004 for AmeriFlux sites and 2004 for the coterminous United States. We retained the 8-day time step consistent with many MODIS products (LST and SWR but 16-day for EVI) and assumed that land cover was stable in 2000–2004. Spatially, we chose a resolution of 7 km and resampled and/or reprojected data for the coterminous United States accordingly. Our rationale for the 7 km choice is based on several criteria. First, flux tower footprints varies considerably from site to site with an average of roughly 1–3 km$^2$ [*Running et al.*, 1999].

[15] Second, the MODIS ASCII subset project provides a 7 km × 7 km subset around each flux tower as the MODIS

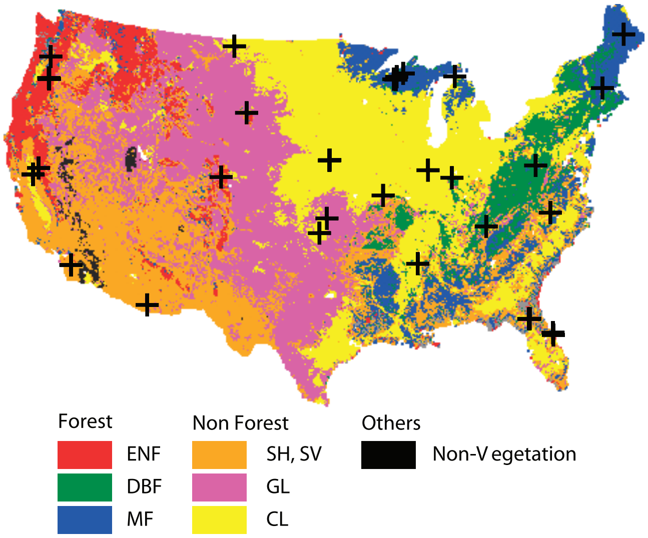


**Figure 1.** Land cover and the distribution of AmeriFlux sites. Land cover was derived from 2001 MODIS land cover products (MOD12Q1) and regrouped into six groups: evergreen needleleaf forest (evergreen needleleaf forest and evergreen broadleaf forest, ENF), deciduous broadleaf forest (deciduous broadleaf forest and deciduous needleleaf forest, DBF), mixed forest (MF), shrubland/savanna (closed/open shrubland and savanna) (SH and SV), grasslands (GL), and croplands (croplands and cropland/natural vegetation mosaic) (CL). The 41 AmeriFlux sites are shown as plus symbols.

footprint for the validation of MODIS products [*Cook et al.*, 2004]. Third, there is no consensus on the most appropriate scale for the generalization from flux towers to large regions. For example, *Rahman et al.* [2005] considered vegetation of a 3 km radius around flux towers homogeneously for the exploration of relationships between EVI and GPP. *Divakarla* [1997] and *Mecikalski et al.* [1999] suggested that flux aggregation errors be minimized at 10 km scale. Considering the flux footprint, the MODIS footprint and existing studies on flux generalization analysis [e.g., *Divakarla*, 1997; *Mecikalski et al.*, 1999; *Rahman et al.*, 2005], we chose 7 km as our spatial resolution for this analysis.

#### 3.2.2. Data Preparation

[16] For LST, we used the MODIS 1 km daytime ORNL ASCII subsets consisting of 7 km × 7 km regions centered on the flux tower for each AmeriFlux site [*Cook et al.*, 2004]. (The ORNL ASCII subsets are not really geographically centered on the flux towers. They only count equal numbers of cells in all rows and columns away from the flux towers, in the sinusoidal projection.). At each time step, we computed flux site LST as the average of the pixels marked as good quality (mandatory quality assurance (QA) flag being zero in the QA data) [*Wan et al.*, 2002]. If none of the 49 values was of good quality, we treated the period as missing. For the coterminous United States, we obtained the MODIS 1 km daytime LST product (MOD11A2) [*Wan et al.*, 2002], which has a deviation of ±1°C compared to ground measurements [*Wan et al.*, 2002, 2004].

[17] For EVI, we again used the subsets for the AmeriFlux sites and the standard MODIS product (MOD13A2) [*Huete et al.*, 2002] for the coterminous United States with negative EVI removed. On the basis of root-mean-square error (RMSE) from ground validations, EVI RMSE is about 0.03 [*Gao et al.*, 2003].

[18] We acquired SWR from daily 0.5° GOES-SRB and processed 8-day averages for both AmeriFlux sites and the coterminous United States. The SWR for each AmeriFlux site was calculated on the basis of the pixel value that is closest to the flux site geographically.

[19] We obtained AmeriFlux land cover from the site descriptions. For the coterminous United States, we obtained 2001 land cover from the MODIS land cover product (MOD12Q1) [*Friedl et al.*, 2002]. MOD12Q1 land cover includes forest (evergreen needleleaf forest, ENF; evergreen broadleaf forest, EBF; deciduous needleleaf forest, DNF; deciduous broadleaf forest, DBF; mixed forest, MF), nonforest (closed/open shrubland, SH; woody savannas and savannas, SV; grassland, GL; cropland and cropland/natural vegetation mixture, CL; permanent wetlands), and nonvegetation (water, urban/built up, snow or ice, barren or sparsely vegetated areas) (Figure 1 and Table 2). On the basis of ground comparisons at the continental scale, the accuracy of MODIS land cover is 70% ~ 85% (M. A. Friedl, 2003, Validation of the consistent-year V003 MODIS land cover product, internal PI document, available at http://www-modis.bu.edu/landcover/userguidelc/consistent.htm).

### 3.3. Methods

[20] We analyzed the representativeness of the AmeriFlux network using remotely sensed LST, SWR and EVI as follows. First, we examined the remotely sensed sample space by generating two-dimensional histograms of LST–SWR, LST–EVI, and SWR–EVI for the 2004 coterminous United States and overlaying the corresponding LST–SWR, LST–EVI, and SWR–EVI from the 2000–2004 AmeriFlux sites. For the 2004 coterminous United States, we used histogram cell sizes of 2°C for LST, 0.5 MJ $m^{-2}$ $d^{-1}$ for SWR, and 0.02 for EVI (dimensionless). Similar to isoline generation, we grouped the histogram frequencies into several ranges and calculated the percentage of pixels in each range. For example, we grouped the frequency of LST–SWR into 0 ~ 5000, 5000 ~ 10000, 10000 ~ 15000, and 15000+. We counted pixels that contributed to each frequency range and then divided the counts by the total number of pixels, yielding the percentage of pixels in each range. For each frequency range in the histograms, we computed the percentage of cells in the histograms that were covered by at least one corresponding 8-day record of (LST, SWR, or EVI) from AmeriFlux sites. We speculate that the AmeriFlux network is unlikely to exhaust the space of LST, SWR and EVI for the coterminous United States, but it should cover at least the core areas (i.e., with high occurrence frequency) of LST, SWR and EVI for the coterminous United States.

[21] Second, we compared the seasonal variations of LST, SWR and EVI from the AmeriFlux sites with those from the coterminous United States. We suspect that if the AmeriFlux network is representative for the ecoregions in the United States, the seasonal signatures of LST, SWR and

**Table 2.** Land Cover, the Corresponding Percentage Coverage in the Coterminous United States and the Number of AmeriFlux Sites for Each Land Cover Used in This Study[a,b]

| Land Cover in This Study | MOD12 Land Cover | Percent Cover in Coterminous United States | Number of AmeriFlux Sites |
|---|---|---|---|
| Evergreen needleleaf forest (ENF) | evergreen needleleaf forest | 6.35 | 12 |
| | evergreen broadleaf forest | 0.69 | |
| Deciduous broadleaf forest (DBF) | deciduous broadleaf forest | 6.43 | 4 |
| | deciduous needleleaf forest | 0.01 | |
| Mixed forest (MF) | mixed forest | 8.65 | 9 |
| shrubland/savanna (SH and SV) | closed shrubland | 0.37 | 4 |
| | open shrublands | 13.99 | |
| | woody savanna | 7.74 | |
| | savanna | 1.65 | |
| Grassland (GL) | grassland | 26.92 | 7 |
| Cropland (CL) | cropland | 20.13 | 5 |
| | cropland/natural vegetation mosaic | 7.02 | |

[a]Excluding water, urban/built up, snow or ice, barren or sparsely vegetated, and unclassified.
[b]Permanent wetlands (0.05%) not shown.

EVI by land cover should be comparable between the AmeriFlux sites and the United States. To facilitate the comparison, we grouped vegetation land cover into six groups (Table 2): ENF, DBF, MF, SH/SV, GL, and CL. We ignored permanent wetlands due to marginal coverage (0.05%) in the coterminous United States. For each land cover and 8-day period, we performed hypothesis testing for the difference in means of the LST, SWR and EVI from AmeriFlux sites and the coterminous United States. We then obtained the confidence interval for the true difference in means at 95% significance level.

[22] Third, we examined the similarity between the coterminous United States and AmeriFlux sites using Euclidian distance (The Euclidian distance between two points $X = (x_1, x_2, \ldots, x_n)$ and $Y = (y_1, y_2, \ldots, y_n)$ is defined as $\sqrt{\sum_n (x_i - y_i)^2}$) in the attribute space (i.e., LST, SWR and EVI). We first scaled LST, SWR and EVI at flux sites to the range of $-1$ and +1 on the basis of their minimum and maximum values in 2000–2004 to eliminate the influence of variables with different absolute magnitudes. We scaled LST, SWR and EVI over the coterminous United States in 2004 accordingly. We then examined two types of similarity: 8-day similarity and seasonal similarity. Eight-day was chosen to correspond to the minimum temporal resolution of the standard MODIS products and reflect the similarity in the finest temporal granularity. On the other hand, time lag is an important phenomenon for many ecosystem processes. Hence, we believe that it is important to investigate the seasonal signatures of the AmeriFlux network and the coterminous United States.

[23] For 8-day similarity (EVI is composited on a 16-day basis; we therefore assigned each 16-day composite EVI to the corresponding two 8-day periods.), we computed the Euclidian distance of 8-day average (LST, SWR and EVI) for each pixel over the coterminous United States to all available observations at flux sites in 2000–2004, a total of 5173 records. We identified the minimum distance and assigned that distance to the corresponding 8-day period and pixel. Finally, we computed the average of the minimum distances (with a maximum possible of 45) for each pixel and used the average as an indicator of how well the ecosystem at that pixel was represented by the AmeriFlux network.

[24] For seasonal similarity, we constructed a time series (LST, SWR, and EVI) using all available 8-day average (LST, SWR, and EVI) grouped by sites and years. We excluded sites and years for which the number of 8-day averages was less than 67% (30 out of a possible 45 periods). Similar to 8-day similarity, we computed the Euclidian distance of the time series (LST, SWR, and EVI) for each pixel over the coterminous United States to all available observations at flux sites in 2000–2004, a total of 107 records. We then identified the minimum distance for each pixel and used the distance as a measure of how well the seasonal variations at that pixel were represented by the AmeriFlux network.

[25] In the process of computing the 8-day and seasonal similarity measures, we kept a tally for each flux site being selected to have the minimum distance to pixels over the coterminous United States. We then computed the percentage of the counts for each flux site and used the percentage as a measure of the representativeness extent of the corresponding flux site.

## 4. Results

[26] Examination of the AmeriFlux sampling space over the coterminous United States revealed that in terms of LST, SWR and EVI, the core regions (i.e., with high occurrence frequency) of the coterminous United States were well represented by the AmeriFlux network (Figure 2 and Tables 3–5). For example, in the LST–SWR sample space, 66.6% of the pixels in the coterminous United States was almost completely covered by AmeriFlux data (Figure 2 and Table 3). Similar patterns were also observed for LST–EVI and SWR–EVI in which LST–EVI had coverage of 87.3–99.3% for 87.2% of the pixels, and SWR–EVI had coverage of 84.6–96.9% for 88.8% of the pixels (Figure 2 and Tables 4–5). The under-represented areas were mostly located over the margins of the sampling space with low occurrence frequency.

[27] Analysis of the seasonal variations of LST for different land covers indicated that the AmeriFlux network had similar distributions of mean LST as the coterminous United States except for ENF where the AmeriFlux LST

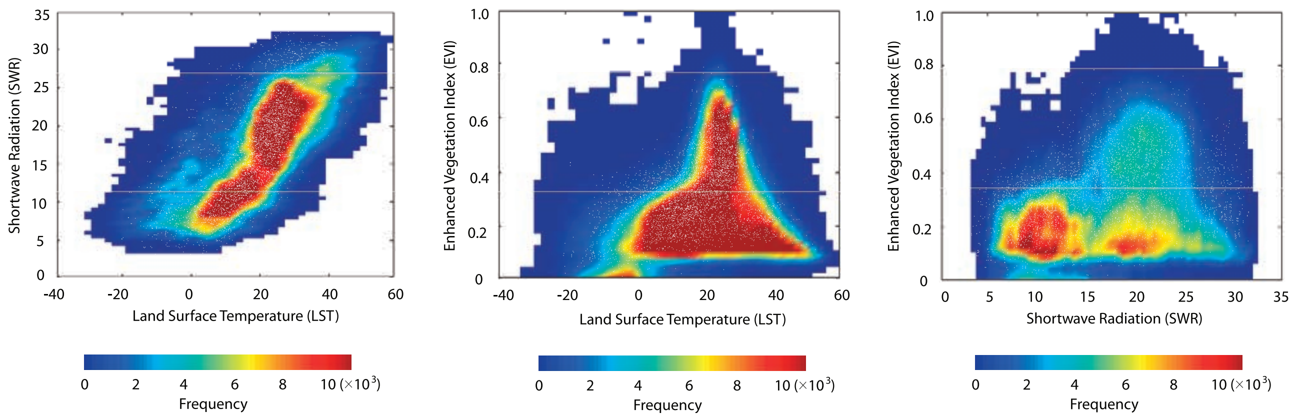


**Figure 2.** Sample spaces of AmeriFlux sites over the coterminous United States for land surface temperature (LST), shortwave radiation (SWR), and enhanced vegetation index (EVI) overlaid on the two-dimensional histograms of LST–SWR, LST–EVI, and SWR–EVI from the coterminous United States. LST and SWR are 8-day averages, and EVI is 16-day composite duplicated for each corresponding 8-day LST and SWR average. The cell sizes for LST–SWR, LST–EVI, and SWR–EVI are (2, 0.5), (2, 0.02), and (0.5, 0.02), respectively. The unit for LST is °C, and the unit for SWR is MJ $m^{-2}$ $d^{-1}$.

was about 2–5°C higher than the coterminous United States during spring and winter (Figure 3). The confidence interval (CI) of ENF also supported this observation where the CI was mostly above the baseline (i.e., with no difference in the means). In addition, the CI was generally wider in spring and winter than in summer and fall for all land covers except shrublands/savanna.

[28] The seasonal variations of AmeriFlux SWR generally followed the pattern of coterminous U.S. SWR (Figure 4). Furthermore, no significant trend/bias was observed in the CI distributions. We suspect that the 0.5 ° SWR from GOES-SRB was too coarse to capture the subtlety between AmeriFlux and the coterminous United States.

[29] The seasonal variations in EVI showed that AmeriFlux EVI was 0.05–0.1 higher than the United States for ENF (Figure 5). The summer AmeriFlux EVI of GL was also ~0.1 higher than the coterminous U.S. EVI. Overall, MF was the most well-represented land cover and DBF is the second in terms of means and CI. Significant bias was observed for ENF and grassland, and great uncertainties were observed for shrublands/savanna and croplands.

[30] Similarity analysis between the flux sites and the coterminous United States revealed distinct patterns between the 8-day and seasonal similarity distributions (Figure 6). The 8-day similarity analysis indicated that New England, the Rocky Mountain ENF, the Sierra Nevada Mountains, the Sonoran Desert, and the coastlines of the Great Lakes were under-represented while the seasonal similarity analysis suggested that the Great Plains (North Dakota and Montana), the Rocky Mountain ENF, and the Great Basin Desert were under-represented. Furthermore, the under-represented regions in the 8-day similarity measure were more clustered toward the western United States while the under-represented regions in the seasonal similarity measure were less regular with sporadic highly under-represented patches spread over the entire coterminous United States.

[31] Examination of the representativeness extents by sites indicates slightly different results using 8-day and seasonal similarity measures (Tables 6–7). When measured with 8-day average similarity, Indiana Morgan Monroe State Forest (MMSF), Indiana (3.97%), Niwot Ridge, Colorado (3.83%), and Walker Branch, Tennessee (3.34%), were among the forest sites with high representativeness extents; while Audubon Research Ranch, Arizona (8.69%), Fort Peck, Montana (6.61%), Bondville, Illinois (6.02%), and Sky Oaks Young Chaparral, California (6.00%), were among the nonforest sites with high representativeness extents. When the seasonal similarity measure was used, the forest sites that had the highest representativeness extents were Harvard Forest, Massachusetts (8.67%), Blodgett, California (6.67%), and Indiana MMSF, Indiana (4.21), while the nonforest sites that had the highest representativeness extents were Sky Oaks young chaparral, California (8.87%), Walnut River, Kansas (8.55%), Goodwin Creek, Mississippi (7.81%), and Fort Peck, Montana (7.68%). Although many sites (e.g., Indiana MMSF, Indiana, Harvard Forest, Massachusetts, Fort Peck, Montana, and

**Table 3.** Statistics for Land Surface Temperature Versus Shortwave Radiation

| | Frequency ($\times 10^3$) | | | |
|---|---|---|---|---|
| | 0 ~ 5 | 5 ~ 10 | 10 ~ 15 | 15+ |
| Percentage of pixels fall in frequency ranges | 33.4 | 27.3 | 23.7 | 15.6 |
| Percentage of cells covered by AmeriFlux data | 42.3 | 98.4 | 100.0 | 100.0 |

**Table 4.** Statistics for Land Surface Temperature Versus Enhanced Vegetation Index

| | Frequency ($\times 10^3$) | | | |
|---|---|---|---|---|
| | 0 ~ 4 | 4 ~ 8 | 8 ~ 12 | 12+ |
| Percentage of pixels fall in frequency ranges | 12.8 | 17.4 | 28.7 | 41.0 |
| Percentage of cells covered by AmeriFlux data | 19.3 | 87.3 | 93.0 | 99.3 |

**Table 5.** Statistics for Shortwave Radiation Versus Enhanced Vegetation Index

| | Frequency ($\times 10^3$) | | | | |
|---|---|---|---|---|---|
| | 0 ~ 2 | 2 ~ 4 | 4 ~ 6 | 6 ~ 8 | 8+ |
| Percentage of pixels fall in frequency ranges | 11.2 | 26.3 | 32.1 | 17.8 | 12.6 |
| Percentage of cells covered by AmeriFlux data | 28.7 | 84.6 | 92.5 | 96.9 | 95.8 |

Sky Oaks Young Chaparral, California) were shown having great representativeness extents in both 8-day and seasonal similarity analysis, other sites (e.g., Blodgett, California, and Bondville, Illinois) had changes in the representativeness extents, likely caused by the different temporal structures used in the 8-day and seasonal similarity analysis resulting in a similar shift in patterns as for Figure 6.

## 5. Discussions

[32] Sampling space analysis of LST, SWR and EVI revealed that the core regions (i.e., with high occurrence frequency) of the coterminous United States were well represented by the AmeriFlux network (Figure 2 and Tables 3–5). The under-represented regions were mostly located over the margins of the sampling space with low occurrence frequency. These observations support the findings of *Hargrove et al.* [2003] that overall the coterminous United States is well-represented by the AmeriFlux network.

[33] Analysis of the seasonal variations of LST, SWR and EVI showed that EVI had the widest CI, indicating great uncertainties in EVI measurements and potentially an under-representation of flux sites in terms of vegetation structures (Figures 3–5). No significant trend/bias was observed for SWR, likely because of the 0.5° SWR from GOES-SRB SWR being too coarse to capture the subtlety between flux sites and the coterminous United States. AmeriFlux network had a good representation of mean LST for the coterminous United States except for ENF where the AmeriFlux LST was higher than the coterminous United States for most of the year. AmeriFlux EVI for ENF was also higher than the coterminous United States, indicating the difficulties associated with ENF studies despite a large number of flux sites being deployed for ENF (12 out of 41) (Table 2).

[34] The similarity analysis between the flux sites and the coterminous United States revealed distinct patterns between the 8-day and seasonal similarity distributions (Figure 6). The discrepancy can be explained as follows. First, the 8-day similarity is an optimistic estimation. For example, even if two locations have very distinct seasonal variations, it is still possible that one 8-day (LST, SWR, and EVI) in the first location will have a small distance to a temporally disjointed 8-day (LST, SWR, and EVI) in the second location because of time lags. On the basis of this measure, the vast majority of the eastern United States was well represented by the AmeriFlux network. On the other hand, the seasonal similarity is a more realistic measure that considers two locations as most similar if the distance of the

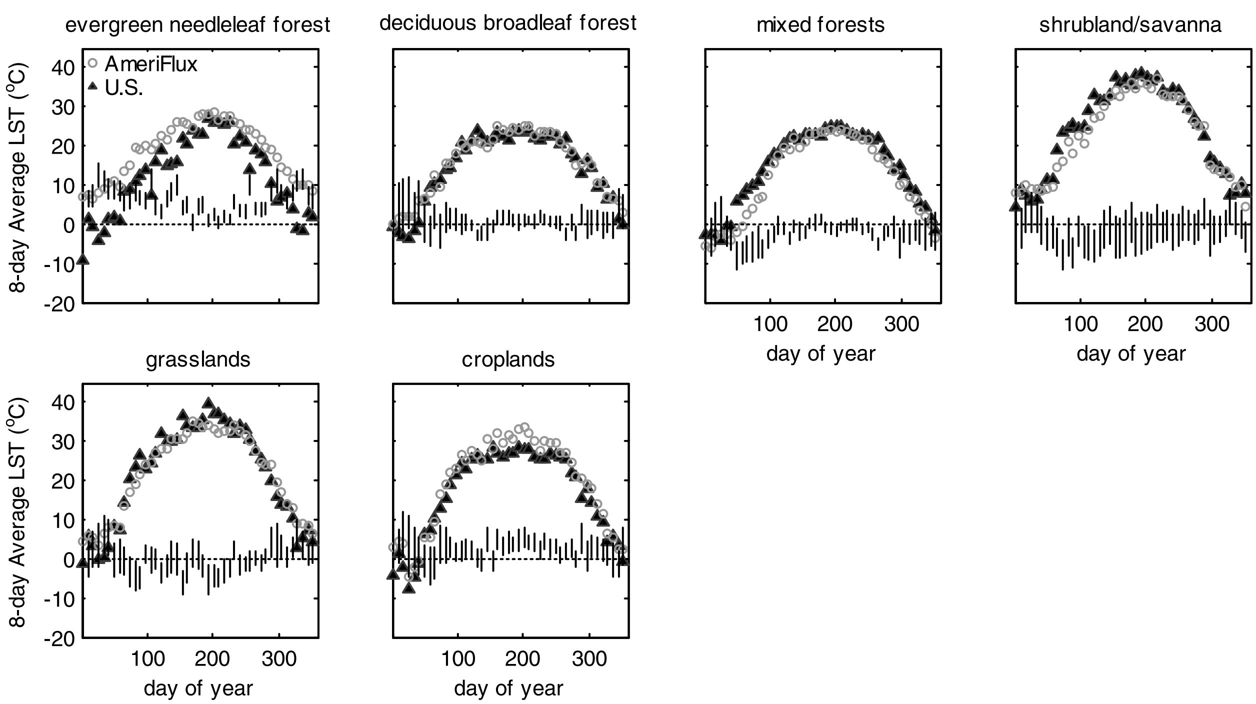


**Figure 3.** Comparison of the seasonal variations of 8-day average LST across the coterminous United States and the AmeriFlux sites by land cover. The coterminous U.S. data were for 2004 and were averaged by land cover. The AmeriFlux data were for 2000–2004 and were averaged by land cover and year of day. The vertical bars indicate the confidence interval for the true difference in means between AmeriFlux sites and the coterminous United States. The dashed line indicates the baseline of no difference.

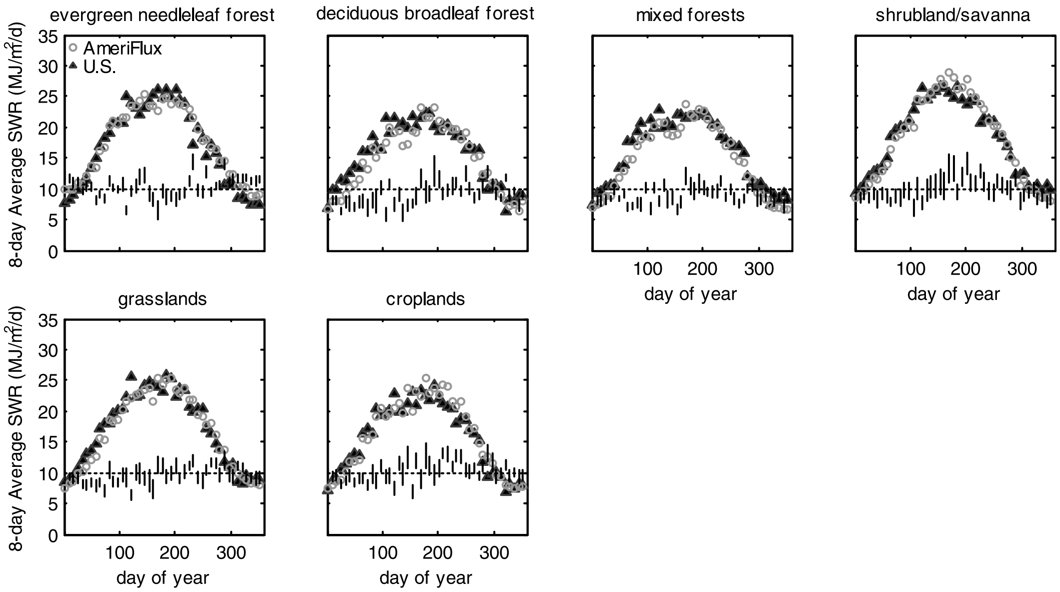


**Figure 4.** Comparison of the seasonal variations of 8-day average SWR across the coterminous United States and the AmeriFlux sites by land cover. The coterminous U.S. data were for 2004 and were averaged by land cover. The AmeriFlux data were for 2000–2004 and were averaged by land cover and year of day. The vertical bars indicate the confidence interval for the true difference in means between AmeriFlux sites and the coterminous United States. An arbitrary number of 10 MJ m$^{-2}$ d$^{-1}$ was added to the confidence interval as a baseline for display purpose. The dashed line indicates the baseline of no difference.

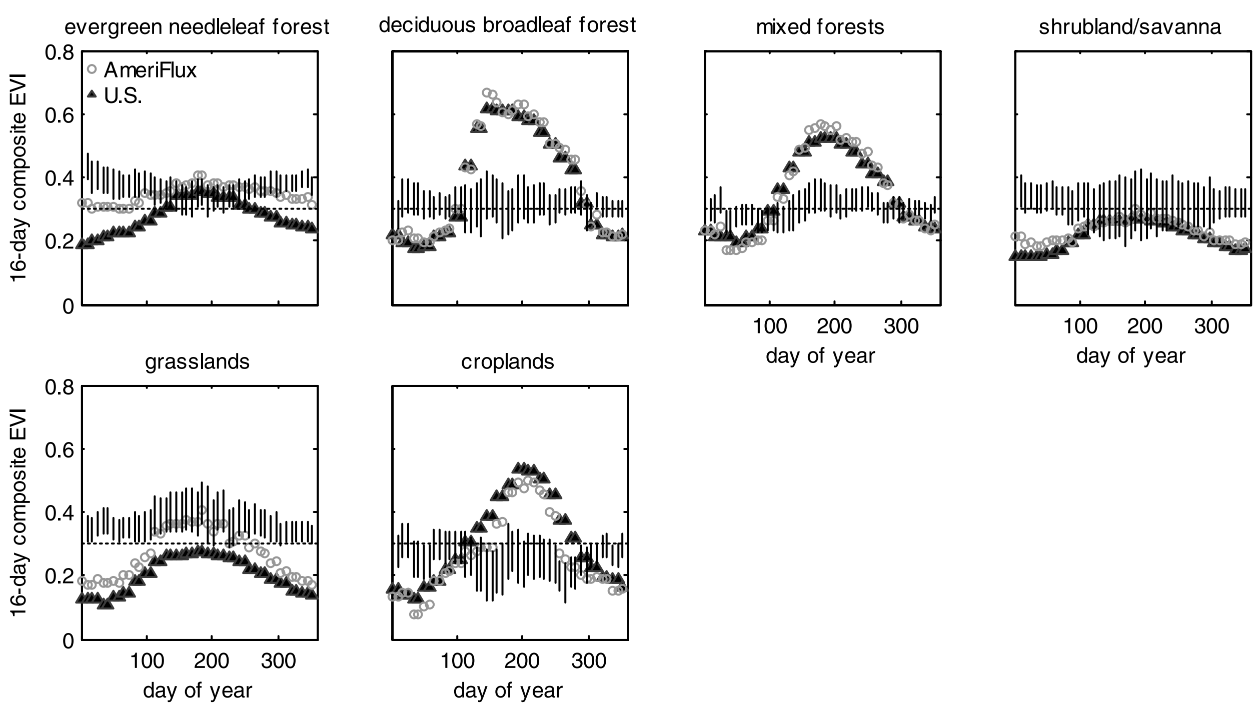


**Figure 5.** Comparison of the seasonal variations of 16-day composite EVI across the coterminous United States and the AmeriFlux sites by land cover. The coterminous U.S. data were for 2004 and were averaged by land cover. The AmeriFlux data were for 2000–2004 and were averaged by land cover and year of day. The vertical bars indicate the confidence interval for the true difference in means between AmeriFlux sites and the coterminous United States. An arbitrary number of 0.03 (unitless) was added to the confidence interval as a baseline for display purpose. The dashed line indicates the baseline of no difference.

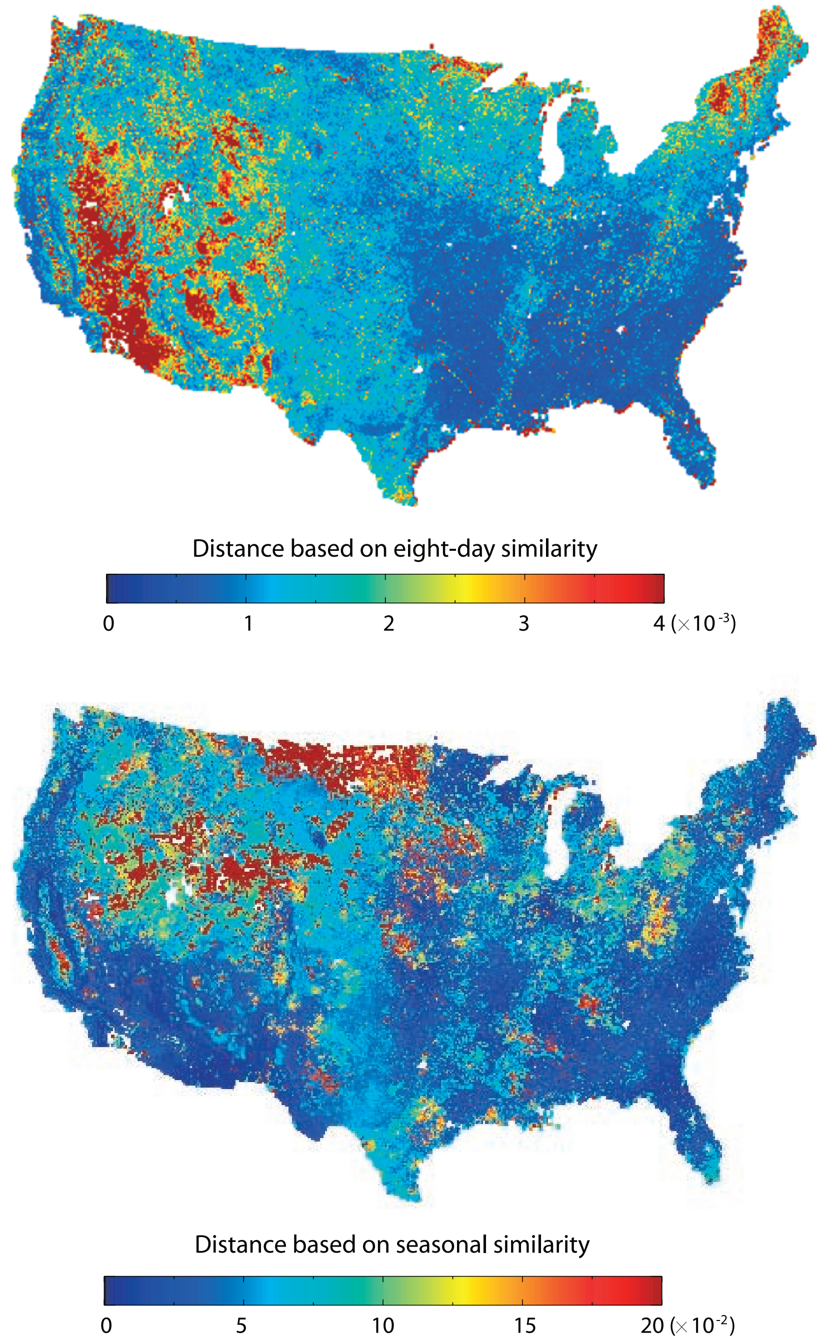


**Figure 6.** Representativeness of the AmeriFlux network over the conterminous United States measured with 8-day average (LST, SWR, and EVI) similarity (top) and seasonal (LST, SWR, and EVI) similarity (bottom). The distances are Euclidean distance measured in the attribute space (LST, SWR, and EVI), and the smaller the distance, the more similar between the AmeriFlux network and the United States.

entire time series of (LST, SWR, and EVI) is small. Thus, even if the seasonal signatures of two locations only differ by a time lag, these two locations are unlikely to be similar under the seasonal similarity measure; however, they may then show high similarity under the 8-day similarity measure. We suspect that this is likely the cause of the sporadic highly under-represented patches in the seasonal similarity distribution. The discrepancy between the 8-day and seasonal similarity distributions implies that more independent studies on the AmeriFlux network representativeness are necessary. As such, users are highly recommended to carefully consider the temporal structure in flux-related model design and data analysis as the representativeness of the AmeriFlux network might vary with the temporal structure.

[35] Overall, both the 8-day similarity and the seasonal similarity indicate that the vast majority of the coterminous United States is well-represented by the AmeriFlux network. Furthermore, the eastern United States is better

**Table 6.** Name and Representative Extent in Percentage for Each Flux Site in This Study Using 8-Day Similarity Measure

| Name | Percent |
|---|---|
| *Forest* | |
| Indiana MMSF, Indiana | 3.97 |
| Niwot Ridge forest, Colorado | 3.83 |
| Walker Branch, Tennessee | 3.34 |
| Willow Creek, Wisconsin | 2.87 |
| Park Falls, Wisconsin | 2.72 |
| Harvard Forest, Massachusetts | 2.47 |
| Duke Forest pine, North Carolina | 2.43 |
| Mize, Florida | 2.29 |
| University of Michigan, Michigan | 2.11 |
| KSC scrub oak, Florida | 2.10 |
| Donaldson, Florida | 1.97 |
| Duke Forest hardwoods, North Carolina | 1.86 |
| Sylvania Wilderness Area, Michigan | 1.85 |
| Austin Cary, Florida | 1.78 |
| Blodgett, California | 1.66 |
| Black Hills, South Dakota | 1.54 |
| Wind River, Washington | 1.46 |
| Metolius intermediate, Oregon | 1.33 |
| Metolius old young, Oregon | 1.29 |
| Howland Forest west, Maine | 1.23 |
| Howland Forest, Maine | 1.06 |
| Ozark, Missouri | 0.43 |
| KSC slash pine, Florida | 0.33 |
| Metolius old, Oregon | 0.26 |
| Howland Forest harvest, Maine | 0.00 |
| Total | 46.20 |
| *Nonforest* | |
| Audubon Research Ranch, Arizona | 8.69 |
| Fort Peck, Montana | 6.61 |
| Bondville, Illinois | 6.02 |
| Sky Oaks young chaparral, California | 6.00 |
| Sky Oaks old chaparral, California | 3.97 |
| Walnut River, Kansas | 3.27 |
| Mead rainfed, Nebraska | 3.22 |
| ARM Oklahoma, Oklahoma | 3.18 |
| Lost Creek, Wisconsin | 2.68 |
| Mead irrigated, Nebraska | 2.47 |
| Mead rotation, Nebraska | 1.91 |
| Tonzi Ranch, California | 1.90 |
| Vaira Ranch, California | 1.72 |
| Goodwin Creek, Mississippi | 1.62 |
| Canaan Valley, West Virgina | 0.53 |
| Duke Forest openfield, North Carolina | 0.00 |
| Total | 53.80 |

represented than the western United States. These results are generally consistent with the findings of *Hargrove et al.* [2003] but discrepancies exist regarding areas being under-represented by AmeriFlux: New England, the Pacific North-west and the Rocky Mountain ENF disagree in the 8-day similarity analysis; the Pacific Northwest, the Great Plains (North Dakota and Montana), the Rocky Mountain ENF, the Sierra Nevada Mountains, the Sonora desert, and the coast-lines of the Great Lakes disagree in the seasonal similarity analysis.

[36] We suspect the discrepancies are mainly due to (1) vegetation structure was not included in the work of *Hargrove et al.* [2003]; (2) the variables used by *Hargrove et al.* [2003] were either static (elevation, soil nitrogen, organic matter, water capacity, frost-free days, soil bulk density and depth, solar aspect and insolation) or smoothed by time (mean and extremes of annual temperature, and mean monthly precipitation); therefore similarities in the time domain was not well captured by *Hargrove et al.* [2003]; and (3) our analysis was synoptic during the growing season. The discrepancies strongly suggest further studies are necessary in accurately identifying areas under-represented by the AmeriFlux network. Such studies will have great operational importance as guidance for future site expansion.

[37] Our site representativeness analysis (Tables 6–7) indicated that while many sites (e.g., Indiana MMSF, Indiana, Harvard Forest, Massachusetts, Fort Peck, Montana, and Sky Oaks Young Chaparral, California) were shown having great representativeness extents in both 8-day and seasonal similarity analysis, other sites (e.g., Blodgett, California, and Bondville, Illinois) had changes in the representativeness extents. We suspect that the different temporal structures used in the 8-day and seasonal similarity analysis result in a similar shift in patterns as discussed for Figure 6. Thus, potential users have to be cautious in drawing conclusions on the spatial representativeness of different sites because the extent might change because of

**Table 7.** Name and Representative Extent in Percentage for Each Flux Site in This Study Using Seasonal Similarity Measure

| Name | % |
|---|---|
| *Forest* | |
| Harvard Forest, Massachusetts | 8.67 |
| Blodgett, California | 6.67 |
| Indiana MMSF, Indiana | 4.21 |
| Sylvania Wilderness Area, Michigan | 3.97 |
| Niwot Ridge forest, Colorado | 3.17 |
| Mize, Florida | 2.64 |
| Wind River, Washington | 2.63 |
| Walker Branch, Tennessee | 2.09 |
| Willow Creek, Wisconsin | 1.54 |
| Duke Forest pine, North Carolina | 1.39 |
| Duke Forest hardwoods, North Carolina | 1.31 |
| Park Falls, Wisconsin | 1.04 |
| Metolius intermediate, Oregon | 1.00 |
| Austin Cary, Florida | 0.97 |
| KSC scrub oak, Florida | 0.79 |
| Howland Forest west, Maine | 0.69 |
| Metolius old, Oregon | 0.49 |
| Metolius old young, Oregon | 0.48 |
| Donaldson, Florida | 0.46 |
| Black Hills, South Dakota | 0.46 |
| Howland Forest, Maine | 0.39 |
| University of Michigan, Michigan | 0.07 |
| Howland Forest harvest, Maine | 0.00 |
| Ozark, Missouri | n/a |
| KSC slash pine, Florida | n/a |
| Total | 45.43 |
| *Nonforest* | |
| Sky Oaks young chaparral, California | 8.87 |
| Walnut River, Kansas | 8.55 |
| Goodwin Creek, Mississippi | 7.81 |
| Fort Peck, Montana | 7.67 |
| Audubon Research Ranch, Arizona | 6.12 |
| Sky Oaks old chaparral, California | 5.34 |
| Mead rainfed, Nebraska | 3.39 |
| Mead irrigated, Nebraska | 1.66 |
| Bondville, Illinois | 1.52 |
| ARM Oklahoma, Oklahoma | 0.93 |
| Vaira Ranch, California | 0.79 |
| Lost Creek, Wisconsin | 0.80 |
| Mead rotation, Nebraska | 0.66 |
| Tonzi Ranch, California | 0.44 |
| Duke Forest openfield, North Carolina | 0.00 |
| Canaan Valley, West Virginia | n/a |
| Total | 54.57 |

the temporal structures used for the representativeness estimation. Furthermore, some flux sites might be established exclusively to capture or validate certain ecosystem behaviors which do not have broad spatial representativeness, but are indispensable for understanding ecosystem behaviors.

## 6. Conclusions

[38] We examined the representativeness of the AmeriFlux network by comparing remotely sensed climate and vegetation variables of the coterminous United States with those at the AmeriFlux network. We found that the AmeriFlux network was generally representative for the coterminous United States but that the eastern United States was better represented than the western United States. Results are generally consistent with the study of *Hargrove et al.* [2003] but discrepancies existed regarding areas being under-represented by the AmeriFlux network, especially in the Pacific Northwest, the Great Plains, New England, the Rocky Mountain evergreen needleleaf forest, and the Sierra Nevada Mountains, suggesting that further studies are necessary in pinpointing areas being under-represented by the AmeriFlux network. Furthermore, our analysis suggested that Indiana MMSF, Indiana, and Harvard Forest, Massachusetts, were among the forest sites with high representativeness extents while Audubon Research Ranch, Arizona, and Sky Oaks Young Chaparral were among the nonforest sites with high representativeness extents.

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