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Calibration of remotely sensed, coarse resolution NDVI to CO_2 fluxes in a sagebrush–steppe ecosystem

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Abstract

The net ecosystem exchange (NEE) of carbon flux can be partitioned into gross primary productivity (GPP) and respiration (R). The contribution of remote sensing and modeling holds the potential to predict these components and map them spatially and temporally. This has obvious utility to quantify carbon sink and source relationships and to identify improved land management strategies for optimizing carbon sequestration. The objective of our study was to evaluate prediction of 14-day average daytime CO_2 fluxes (F_{day}) and nighttime CO_2 fluxes (R_n) using remote sensing and other data. F_{day} and R_n were measured with a Bowen ratio–energy balance (BREB) technique in a sagebrush (*Artemisia* spp.)–steppe ecosystem in northeast Idaho, USA, during 1996–1999. Micrometeorological variables aggregated across 14-day periods and time-integrated Advanced Very High Resolution Radiometer (AVHRR) Normalized Difference Vegetation Index (iNDVI) were determined during four growing seasons (1996–1999) and used to predict F_{day} and R_n. We found that iNDVI was a strong predictor of F_{day} ($R^2 = 0.79$, $n = 66$, $P < 0.0001$). Inclusion of evapotranspiration in the predictive equation led to improved predictions of F_{day} ($R^2 = 0.82$, $n = 66$, $P < 0.0001$). Crossvalidation indicated that regression tree predictions of F_{day} were prone to overfitting and that linear regression models were more robust. Multiple regression and regression tree models predicted R_n quite well ($R^2 = 0.75-0.77$, $n = 66$) with the regression tree model being slightly more robust in crossvalidation. Temporal mapping of F_{day} and R_n is possible with these techniques and would allow the assessment of NEE in sagebrush–steppe ecosystems. Simulations of periodic F_{day} measurements, as might be provided by a mobile flux tower, indicated that such measurements could be used in combination with iNDVI to accurately predict F_{day}. These periodic measurements could maximize the utility of expensive flux towers for evaluating various carbon management strategies, carbon certification, and validation and calibration of carbon flux models.
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1. Introduction

Increasing atmospheric CO_2 concentrations and their potential impacts on global change are the subject of widespread studies, political debates, and international discussions. Although the status of carbon stocks in both biomass and soil organic matter has been estimated for various ecosystems (Fallon et al., 1998; Gilmanov & Oechel, 1995; Hunt, Lavigne, & Franklin, 1999), CO_2 fluxes from these ecosystems and their driving forces are not well understood either locally or globally (Cihlar et al., 2002). Discussions to reduce or curtail the rate of atmospheric CO_2 increases (Fallon et al., 1998; Pfaff et al., 2000) have suggested that terrestrial (biological) sinks might be used to partially offset industrial CO_2 sources in a global market system for carbon sequestration. The possible effectiveness of these terrestrial sinks and the quantitative estimates of their "sink strengths" have relied mainly on measurements of changes in carbon stocks.

Recent developments in measurement techniques for assessing CO_2 fluxes provide tools for quantifying the net

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ecosystem exchange (NEE) of CO_2 on a continuous, daily basis at point sources. The potential value of these near real-time measurements to quantify CO_2 flux rates, their driving forces, and annual fluxes has resulted in integrated research efforts across a variety of land-cover and land-use types as seen in the Ameriflux Network (Desjardins, Hart, Macpherson, Schuepp, & Verma, 1992), Euroflux Network (Aubinet et al., 2000), and a network of rangeland ecosystem sites in the western USA established by the U.S. Department of Agriculture's Agricultural Research Service (USDA-ARS) (Svejcar, Mayeux, & Angell, 1997). Sole reliance on field point samples can lead to biased regional estimates of CO_2 fluxes or production (Biondini, Lauenroth, & Sala, 1991; Rahman, Gamon, Fuentes, Roberts, & Prentiss, 2001). The extrapolation of site-specific data across broad spatial scales requires a modeling approach to extend the site-specific algorithms to similar land-cover types (Reich et al., 1999; Running et al., 1999; Vourlitis et al., 2000). Establishing these relationships could be the basis for mapping CO_2 fluxes across landscapes and regions, and could assist in evaluating various land-use management alternatives to optimize carbon sequestration, including sink development (Bounoua et al., 2000; Fallon et al., 1998; Gilmanov & Oechel, 1995; Kelly, Hunt, Reiners, Smith, & Welker, 2002; Prince & Steininger, 1999; Tucker, Fung, Keeling, & Gammon, 1986; Williams, Eugster, Rastetter, McFadden, & Chapin, 2000).

Quantification of carbon fluxes, either in natural systems or under different management scenarios, can be accomplished across extended time periods by assessment of carbon stocks (Bliss, Waltman, & Petersen, 1995; Fallon et al., 1998; Gilmanov & Oechel, 1995) or across annual time periods by measurement of CO_2 fluxes with micrometeorological techniques such as eddy covariance and Bowen ratio–energy balance (BREB) methods (Frank & Dugas, 2001; Rosenberg, 1983; Sims & Bradford, 2001). Micrometeorological approaches for estimating CO_2 fluxes, including the eddy covariance technique and the BREB method, provide a means to estimate CO_2 flux at specific sites. A detailed description of micrometeorological and the theories behind them can be found in Moncrieff, Valentini, Greco, Seufert, and Ciccioli (1997). The eddy covariance technique is a direct method of measuring fluxes and measures vertical wind speed, wind direction, and CO_2 concentration of air moving past a sampling point. The eddy covariance method is advantageous because it is a direct method of measurement; however, this method requires electronically sophisticated equipment. Additionally, recent studies indicate that energy fluxes such as net radiation (NR) and soil heat flux should be determined concurrently with eddy covariance measurements to correct fluxes for lack of energy balance closure (Twine et al., 2000).

Indirect methods of measuring CO_2 fluxes include the aerodynamic and BREB techniques, which quantify the rate of diffusion down a concentration gradient. The aerodynamic method has the advantage that it uses simple instrumentation, but the technique has limitations within canopies or in canopies with small gradients (Raupach, 1988). The BREB technique is based on the law of energy conservation and has been used extensively to determine the components of energy balance and evapotranspiration as well as CO_2 fluxes above various crop canopies (e.g., Baldocchi, Verma, & Rosenberg, 1981; Dugas et al., 1991; Dugas, Heuer, & Mayeux, 1999; Frank & Dugas, 2001; Kim, Verma, & Rosenberg, 1989; Sims & Bradford, 2001; Verma & Rosenberg, 1975). The BREB method is advantageous because it uses simpler sensors than eddy covariance techniques, but is difficult to apply during periods when net radiation and gradients in temperature are small (e.g., at sunrise and sunset). Nevertheless, these micrometeorological techniques have been well validated during the past 30 years (Moncrieff et al., 1997). Although eddy correlation and BREB techniques have shown acceptable agreement in semiarid environments (Unland, Houser, Shuttleworth, & Yang, 1996), reliable surface energy fluxes were easier to determine with the BREB method, but the eddy covariance method provided greater accuracy for short time periods.

Modeled estimates of carbon fluxes or other biophysical parameters can be mapped over regions using either physical models (Kohlmaier et al., 1997; Pan et al., 1998; Randall, Dazlich, Zhang, & Denning, 1996) or empirical statistical models (Paruelo, Epstein, Lauenroth, & Burke, 1997; Wylie, Harrington, Prince, & Denda, 1991). Statistical models can reveal new useful relationships (De'ath & Fabricius, 2000; Prince & Steininger, 1999) and are simple, easily constructed, and work with relative or surrogate input layers. Statistical techniques represent the population from which the training samples were taken, but may be erroneous when extrapolated beyond the range (data values, time, and space) of the training data (Asner & Wessman, 1997; Hall, Knapp, & Huemmrich, 1997). Functional models are often complex, include numerous assumptions, and require accurate data inputs calibrated to standard physical units (Bonan, 1995; Gilmanov, Parton, & Ojima, 1997; Hall et al., 1997; Liu et al., 2002). Functional models typically perform better than statistical models on unique or new circumstances, but intensive input requirements often are a major constraint. Functional models allow assessment of long-term trends and can be used to evaluate various input scenarios. Innovative combinations of remote sensing and functional models have proven useful (Asner, Bateson, Privette, El Saleous, & Wessman, 1998; Asner & Wessman, 1997; Field, Randerson, & Malmstrom, 1995; Liu et al., 2002; Pfaff et al., 2000; Potter et al., 1993; Reich, Turner, & Bolstad, 1999; Sellers et al., 1997; Williams et al., 2000). Regional estimation and mapping of CO_2 flux should utilize simple algorithms (Reich et al., 1999) with remote sensing input (Field, Gamon, & Penuelas, 1994; Hall, Townsend, & Engman, 1995; Kelly et al., 2002; Reich et al., 1999; Vourlitis et al., 2000).

Advanced Very High Resolution Radiometer (AVHRR) Normalized Difference Vegetation Index (NDVI) data are

well suited for studies of ecosystem dynamics from regional to global scales. NDVI has successfully tracked biophysical variables (Bartlett, Whitting, & Hartman, 1990; Chen & Brutsaert, 1998; Purevdorj, Tateishi, Ishiyama, & Honda, 1998; Seen, Mougin, Rambal, Gaston, & Hiernaux, 1995; Wylie et al., 1991; Wylie, Meyer, Tieszen, & Mannel, 2002), production (Gilabert, Masellin, Conese, & Bindi, 1995; Paruelo et al., 1997), and CO_2 fluxes (Bartlett et al., 1990; Cihlar, Caromori, Schuepp, Desjardins, & MacPherson, 1992; Mack, Desjardins, MacPherson, & Schuepp, 1990; Oechel et al., 2000) in grasslands and shrublands. However, the decoupling of CO_2 flux and the vegetation indices were observed in the boreal forest and attributed to very low radiation use efficiency (RUE) of coniferous evergreens, incomplete accounting of below canopy production, and canopy clumpiness (Gower, Kucharik, & Norman, 1999; Loechel et al., 1997). The integration of remotely sensed and CO_2 flux data could provide a more efficient and accurate modeling and prediction of carbon fluxes at the landscape and regional levels.

A widely spaced network of eddy covariance or BREB flux towers would be required to insure model robustness (Cihlar et al., 2002; Cohen & Justice, 1999; Reich et al., 1999; Running et al., 1999) and to minimize spatial autocorrelation effects for regional mapping with statistical models using remote sensing and GIS (Cairns, 2001). However, networks of permanently located flux towers are expensive to operate and maintain. Mobile flux towers in combination with remote sensing techniques and meteorological data may help maximize the utility of flux towers. Certification of carbon sequestration activities (Gustavsson et al., 2000) could be monitored using mobile flux towers combined with remote sensing and models to predict fluxes when the tower is offsite. This approach could be used to both increase CO_2 flux data for model development and improve the spatial representation of those data. The objective of our study was to evaluate if remotely sensed NDVI can be used to predict CO_2 fluxes in a sagebrush–steppe ecosystem in central Idaho, USA, and to determine if less frequent measurements could accurately predict continuously measured CO_2 fluxes.

2. Theory

The instantaneous rate of CO_2 flux or NEE can be described in two alternative ways. NEE can be described as the difference between gross primary productivity (GPP) and respiration (R):

$$NEE = GPP - R \qquad (1)$$

which facilitates a better understanding of carbon balances (Choudhury, 2000, 2001). In terms of the dynamics of the total ecosystem carbon stock (C_t), NEE may be described as:

$$NEE = dC/dt + E \qquad (2)$$

where C is carbon density in an ecosystem, t is time, and E denotes the rate of soil erosion, which can be significant such as when grassland is converted to shrubland (Parizek, Rostagno, & Sottini, 2002). The combination of flux tower measurements (Eq. (1)) with the dynamics of carbon stock assessment (Eq. (2)) opens the possibility of being able to evaluate rates of soil erosion even in those cases when direct experimental measurements of E are difficult.

The conceptual basis for modeling GPP is often Monteith's equation or the radiation use efficiency (RUE) model (Field et al., 1995; Kelly et al., 2002; Monteith, 1977; Paruelo et al., 1997; Potter et al., 1993; Rahman et al., 2001). The RUE model defines the components of GPP for a given time period as total absorbed photosynthetically active radiation (APAR) and the RUE coefficient (ε):

$$GPP = \varepsilon \ APAR \qquad (3)$$

APAR can be derived from photosynthetically active radiation (PAR) reaching the Earth's surface (Lopez, Rubio, Martinez, & Batlles, 2001) and the fraction of PAR absorbed by plants (fPAR):

$$APAR = PAR \times fPAR \qquad (4)$$

Relationships between remotely sensed data and fPAR have been developed (Bartlett et al., 1990; Chen, 1996; Gamon et al., 1995; Knyazikhin et al., 1999; Tieszen, Reed, Bliss, Wylie, & DeJong, 1997; Wylie et al., 2002) and may facilitate regional mapping of NEE and rangeland production (Reeves, Winslow, & Running, 2001; Wylie et al., 1991). The RUE framework may be useful in estimating net primary production (NPP) (Turner et al., 2002) and CO_2 fluxes, but must be carefully quantified (Gamon et al., 1995) and may introduce regional biases (Choudhury, 2001). Drought (Bartlett et al., 1990; Hanan, Prince, & Begue, 1995; Jamieson, Martin, Francis, & Wilson, 1995), photosynthetic pathway type (C_3 versus C_4; Hanan, Prince, & Begue, 1997), variations in PAR (Rahman et al., 2001), and land cover/vegetation structure (Asner et al., 1998; Gower et al., 1999; Mack et al., 1990) affect the value of ε.

The linear relationship between NPP or NEE and time-integrated NDVI (iNDVI) (Seen et al., 1995) was principally driven by their relationship to GPP. Mapping of GPP or surrogates, such as daytime fluxes (F_{day}), can be estimated with remote sensing as one of the inputs (Reeves et al., 2001; Vourlitis et al., 2000). Mapping of CO_2 sources and sinks and their strengths (NEE) requires that R must also be mapped because GPP and R do not necessarily covary (Anthoni, Law, & Unsowrth, 1999; Law, Williams, Anthoni, Baldocchi, & Unsworth, 2000). Because the functional relationships are different for GPP and R, Choudhury

(2001) estimated daytime flux (F_{day}) rather than NEE to minimize the confounding effects of nighttime fluxes (R_n), and Vourlitis et al. (2000) separately mapped GPP and total R. Respiration can be more relevant than GPP in the determination of CO_2 source and sink strengths (Gilmanov, Johnson, & Saliendra, 2003; Valentini et al., 2000).

Although remotely sensed vegetation indices are more closely correlated with GPP, they can help estimate R components associated with autotrophic maintenance and growth R, which are related to live canopy biomass (Li et al., 2002) or GPP. The primary mechanism for predicting and mapping R has been through temperature (Oechel et al., 2000; Potter et al., 1993; Williams et al., 2000), while others have questioned this approach (Glardina & Ryan, 2000). Soil water content or its surrogates also have been shown to be an important variable for predicting R (Mielnick & Dugas, 2000; Raich, Potter, & Bhagawati, 2002; Tufekcioglu, Raich, Isenhart, & Schultz, 2001; Valentini, Gamon, & Field, 1995; Vourlitis et al., 2000), but soil moisture was not always important (Bajracharya, Lal, & Kimbal, 2000). Wind speed also can affect soil CO_2 fluxes associated with R (Massman, Sommerfeld, Mosier, & Zeller, 1997; Rahman et al., 2001; Takle et al., 2000). Others have used R_n, available from flux towers, to estimate daytime R (Rahman et al., 2001; Williams et al., 2000). Hyperbolic light–curve equations can derive GPP and R estimates from flux tower data (Gilmanov et al., in press; Vourlitis et al., 2000), where R would include both nighttime and daytime R.

3. Methods

3.1. Site description

The field site was at the U.S. Sheep Experiment Station (44°16′ N, 112°08′ W), which is located 10 km north of Dubois on the Upper Snake River Plain of northeast Idaho, USA. The site is situated in the northeastern portion of the sagebrush–steppe ecosystem (West, 1983) at an elevation of about 1700 m. The dominant shrub, grass, and forb on the study site were three-tipped sagebrush (*Artemisia tripartita* Rydb.), bluebunch wheatgrass [*Pseudoroegneria spicata* (Pursh) A Löve], and arrowleaf balsamroot [*Balsamorhiza saggitata* (Pursh) Nutt.], respectively. Other important species include green rabbitbrush [*Chrysothamnus viscidiflorus* (Hook.) Nutt.], big sagebrush (*Atremisia tridentata* Nutt.), needle-and-thread grass (*Stipa comata* Trin. and Rupr.), and yarrow (*Achillea millefolium* L.).

Climate at the site is semiarid with cold winters and warm summers. Mean annual precipitation for the area during a 64-year period was 325 mm, which included 70 cm of snow; the area has a mean annual temperature of 6 °C (NOAA, 1993). Temperatures range from 38 °C in summer to − 34 °C in winter with a normal frost-free period of 70– 90 days (Blaisdell, 1958). Soils at the site are loamy and

derived from wind-blown loess, residue, or alluvium (Natural Resource Conservation Service [NRCS], 1995). Soil characteristics are variable across the landscape because of the varying thickness of parent material overlying the basalt bedrock and are composed of three mollisols on slopes ranging from 0% to 12%. With increasing depth and degree of development, soils are classified as Typic Calcixerols (Anatolian series), Pachic Haploxerolls (Maremma series), and Pachic Argixerols (Akbash series).

3.2. Bowen ratio measurements

A relatively undisturbed area (400 × 400 m) surrounded by similar vegetation and soils was fenced in 1995 to exclude grazing, and a BREB system was installed near the center of the enclosure to obtain continuous measurements of CO_2 fluxes and associated micrometeorological characteristics. The theory and operation of the BREB system (Model 023/CO_2 Bowen Ratio; Campbell Scientific) are described in detail by Dugas (1993) and Dugas et al. (1999). Briefly, CO_2 and water vapor concentrations were measured with an infrared gas analyzer (IRGA,[1] Model LI-6262; Li-Cor). Air samples from two heights (0.8 and 1.8 m above the soil surface) were drawn and routed to the IRGA, which measured the CO_2 and water vapor concentration gradients between the two heights. Air temperature gradients at the two heights were simultaneously measured with fine-wire, chromel–constantan thermocouples. The CO_2, water vapor, and temperature gradients were measured every second, and the average gradients were calculated and stored every 20 min with a data logger and storage module (Models 21X and SM192; Campbell Scientific). Fluxes of CO_2, water vapor, and energy were calculated using 20-min averages. The eddy diffusivity, which was assumed equal for heat, water vapor, and CO_2, was calculated from sensible heat flux and temperature gradients. The CO_2 flux was calculated as the product of the eddy diffusivity and CO_2 gradient and corrected for vapor density gradients at the two heights (Webb, Pearman, & Leuning, 1980). The CO_2 fluxes estimated by the BREB technique were shown to be similar to those measured by a closed chamber technique at two sagebrush–steppe sites in the western USA (Angell, Svejcar, Bates, Saliendra, & Johnson, 2001). Various techniques have been used to fill in data gaps that occur in flux tower measurements (Falge et al., 2001). Day-specific solutions of nonlinear light–curve equations derived from the 20-min flux data were used in this study to fill data gaps (Gilmanov et al., in press).

During the 1996–1999 growing seasons, CO_2 flux measurements were summarized as net daytime fluxes (F_{day}), R_n, and net 24-h fluxes (F_{net}). The CO_2 fluxes were also averaged into time intervals that coincided with the

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[1] Any use of trade, product, or firm name is for description purposes only and does not imply endorsement by the U.S. Government.

NDVI biweekly composite periods and integrated across each of these periods. In this study, we used F_{day} as an approximation of GPP, similar to Choudhury (2001), because F_{day} was routinely obtained with the BREB system and F_{day} minimized the confounding effects of R_n, which was estimated separately.

3.3. Satellite data

NDVI data are affected by cloud contamination and atmospheric attenuation, which usually reduce the NDVI value (Los, Justice, & Tucker, 1994). One method of reducing these effects is maximum value compositing (MVC); we used a compositing period of 14 days in our study. A weighted least squares linear regression approach to temporal NDVI smoothing was employed to reduce signal contamination (Swets, Reed, Rowland, & Marko, 1999). We extracted NDVI values for the growing seasons of 1996–1999. To define the start and end of the growing season, we identified a well-defined trend change in NDVI values using a backward-or forward-looking, moving-average technique (Reed et al., 1994). The duration of the growing season was defined as the difference between the start and end of season. Values of NDVI associated with dormant vegetation or soil were used as a baseline to detect changes that indicated the onset of greenness and the end of the growing season. Linear temporal interpolation was used to estimate daily smoothed NDVI, and the respective baseline NDVI was subtracted. This was then summed for the growing season and each 2-week MVC period. The CO_2 fluxes were compared to the time-integrated, smoothed NDVI values (iNDVI) for 2-week periods during the growing season, while iNDVI integrated across the growing season was used for annual comparisons.

3.4. Statistical analysis

Linear regression analysis was used to establish relationships between predictor variables and F_{day} and R_n from the BREB flux tower using the independent variables listed in Table 1. Regression residual plots were visually inspected to assess assumptions of linearity and homogeneity of variance. The robustness of the models across years was tested using interaction and indicator variables with 1998 considered as the standard. The extra sums of squares principal were used to test whether combined year effects of both slope and intercept were significant beyond the sums of squares accounted for by a simple model (Neter, Wasserman, & Kutner, 1983; Wylie, 1991). These multiple dependent tests warranted a conservative level of testing ($P < 0.01$) for year effects.

We were interested in determining if F_{day} and R_n prediction could be improved with the additional meteorological and site variables listed in Table 1 and the subsequent application of regression tree techniques. Although not all of these variables would be easily available as spatial data sets

Table 1
Possible independent variables used to predict daytime (F_{day}) and nighttime CO_2 flux (R_n)

Variables	Regression	Regression tree	Description
iNDVI	X	X	Time-integrated Normalized Difference Vegetation Index
PAR	X	X	Photosynthetically active radiation
ET	X	X	Evapotranspiration
TAIR	X	X	Air temperature
PPT	X	X	Precipitation
VPD	X	X	Vapor pressure deficit
WINDS	X	X	Wind speed
RH	X	X	Relative humidity
NR		X	Net radiation
TSOIL		X	Soil temperature at 4 cm
SOILW		X	Volumetric soil water content

across the landscape, they were quantified at the BREB tower in our study. Regression tree techniques are used to develop relationships and predictions that take nonlinearity into consideration, account for high-order interactions, and effectively use thematic or categorical data (De'ath & Fabricius, 2000). These techniques hierarchically split the data and then allowed development of predictive linear equations for each of the various data subsets. Regression trees are useful for both stratification (Joel, Schimel, Friedl, Davis, & Dubayah, 1994; Prince & Steininger, 1999) and prediction (De'ath & Fabricius, 2000). Three successive regression trees were produced with each successive regression tree attempting to correct prediction errors in the previous regression tree.[2] The regression tree software quantified the number of training observations in each stratum in the regression tree models. The independent regression variables utilized in each stratum or "leaf node" were ordered by decreasing relevance. A program, which quantified the relative frequency of use of a variable in stratification as well as the cumulative relevance rank of all the independent variables for all the regressions, was written. This information was used to summarize multiple and sometimes complex series of successive regression trees.

To test the possibility of using periodic F_{day} data (as might be provided by a mobile flux tower) compared to continuous flux data, we divided our flux data into three subsets (jack-knifing). Each subset simulated a revisit cycle from a mobile flux tower during every third biweekly composite period. Each of the three subsets had different sequential starting biweekly composite periods. Two biweekly composite periods for each subset were withheld from the analysis and used as independent tests for each sequence subset. As a result, regressions and regression trees assessing mobile flux towers were trained on a third of the data and tested on two-thirds of the data and repeated three times.

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[2] See Committee models (www.rulequest.com/cubist-unix.html).

4. Results and discussion

Values of F_{net}, F_{day}, iNDVI, and precipitation (PPT) were summed across NDVI composite periods 9–22 for 1996–1999. F_{net} and F_{day} were positive for all four growing seasons and increased steadily from 1996 to 1999, although iNDVI and PPT were lower in 1999 than 1998 (Fig. 1). Values of F_{net} varied widely during the growing seasons of 1996–1999. R_n, which is the difference between F_{day} and F_{net}, was reduced in 1999 and resulted in a slightly higher F_{net} in 1999 than in 1998. This occurred despite higher PPT and iNDVI values in 1998. The weather characteristics and CO_2 fluxes during the various growing seasons varied greatly during the study, suggesting that the derived models would likely be robust across a wide range of climatic, NDVI, and other input characteristics.

4.1. Daytime CO_2 flux (F_{day})

Linear relationships between MVC iNDVI and F_{day} were strong (R^2 from 0.79 to 0.92) for all years (Fig. 2). MVC periods with low or high precipitation were not associated with underestimation or overestimation of F_{day} from iNDVI. NDVI has been proposed as a surrogate for potential photosynthesis (Yoder & Waring, 1994). Decoupling of potential and actual photosynthesis is typically driven by drought stress or respiration (Gamon et al., 1995; Gower et al., 1999; Law et al., 2000), but this was not readily apparent in our data, despite the wide range in growing season NEE. This may have been attributable to our use of a 14-day MVC period. Estimation of CO_2 fluxes from remotely sensed data may be more problematic for shorter MVC time periods or single days. Based on R^2 and the regression standard error, the strongest relationship between iNDVI and F_{day} occurred in 1996, while the weakest occurred in 1998 (Fig. 2).

To assess the ability of iNDVI to predict the seasonal progression of F_{day}, linear regression analyses were conducted using all years and all biweekly composites with the independent variables presented in Table 1. iNDVI was a strong predictor of F_{day} (Table 2). In the analysis, $C(p)$ criteria (Freund & Littell, 1995) from all possible combinations of independent variables identified iNDVI and ET as the optimal independent variables; however, iNDVI combined with PAR was also a strong predictor of F_{day} ($R^2 = 0.81$). Several methods for estimating spatial distributions of ET, precipitation, and temperature from remotely sensed and ancillary data have been used (Bristow & Campbell, 1984; Caselles, 1993; Choudhury & DiGirolamo, 1998; Kimball, Running, & Nemani, 1997; Thornton & Running, 1999; Xie & Arkin, 1997) and allow spatial mapping of these variables. The simple iNDVI regression model was robust across years, but the multiple regression model had significantly different relationships in 1999. Accounting for significant year effects for 1999 with indicator and interaction terms resulted in unique slope and intercept coefficients (Neter et al., 1983) for 1999 and increased the R^2 value to 0.88 with no significant temporal autocorrelation. The temporal dynamics of iNDVI, ET, PPT, and F_{day} in 1999 (Fig. 3) indicated that early season PPT, or maybe snow melt, may have contributed to deep soil water storage, which the deep-rooted sagebrush and other shrubs probably used later in the hot, dry summer to continue photosynthesis into composite period 13. This peak in F_{day} was not tracked well by iNDVI, indicating either possible increases in RUE or incomplete removal of subpixel cloud effects by compositing and temporal smoothing procedures.

The inclusion of ET in the multiple regression model may somehow correct for variable RUE and R. Bartlett et al. (1990) found that the relationship between NEE and NDVI improved when ambient air temperature was included in the
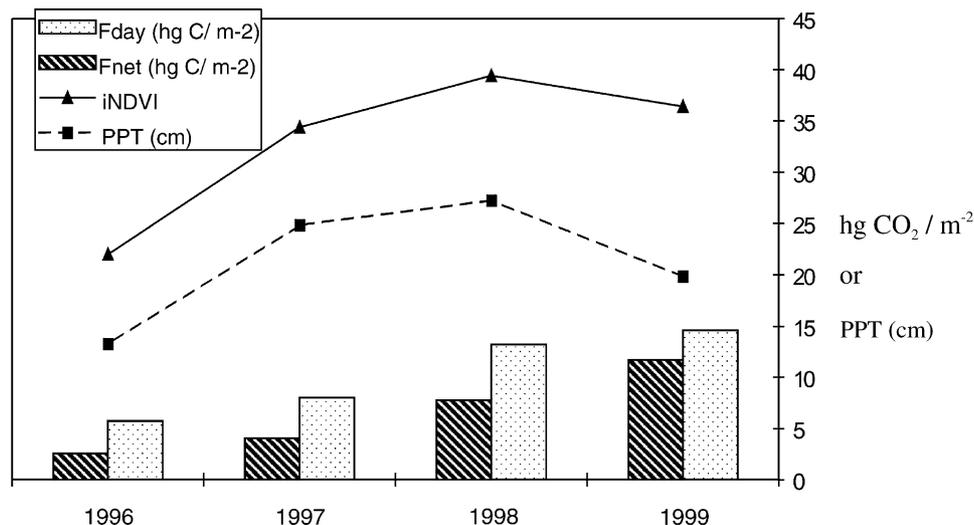

Fig. 1. Cumulative net (F_{net}) and daytime (F_{day}) CO_2 fluxes, integrated NDVI (iNDVI), and precipitation (PPT) across the growing season (March–July) for the 4 years of our study.
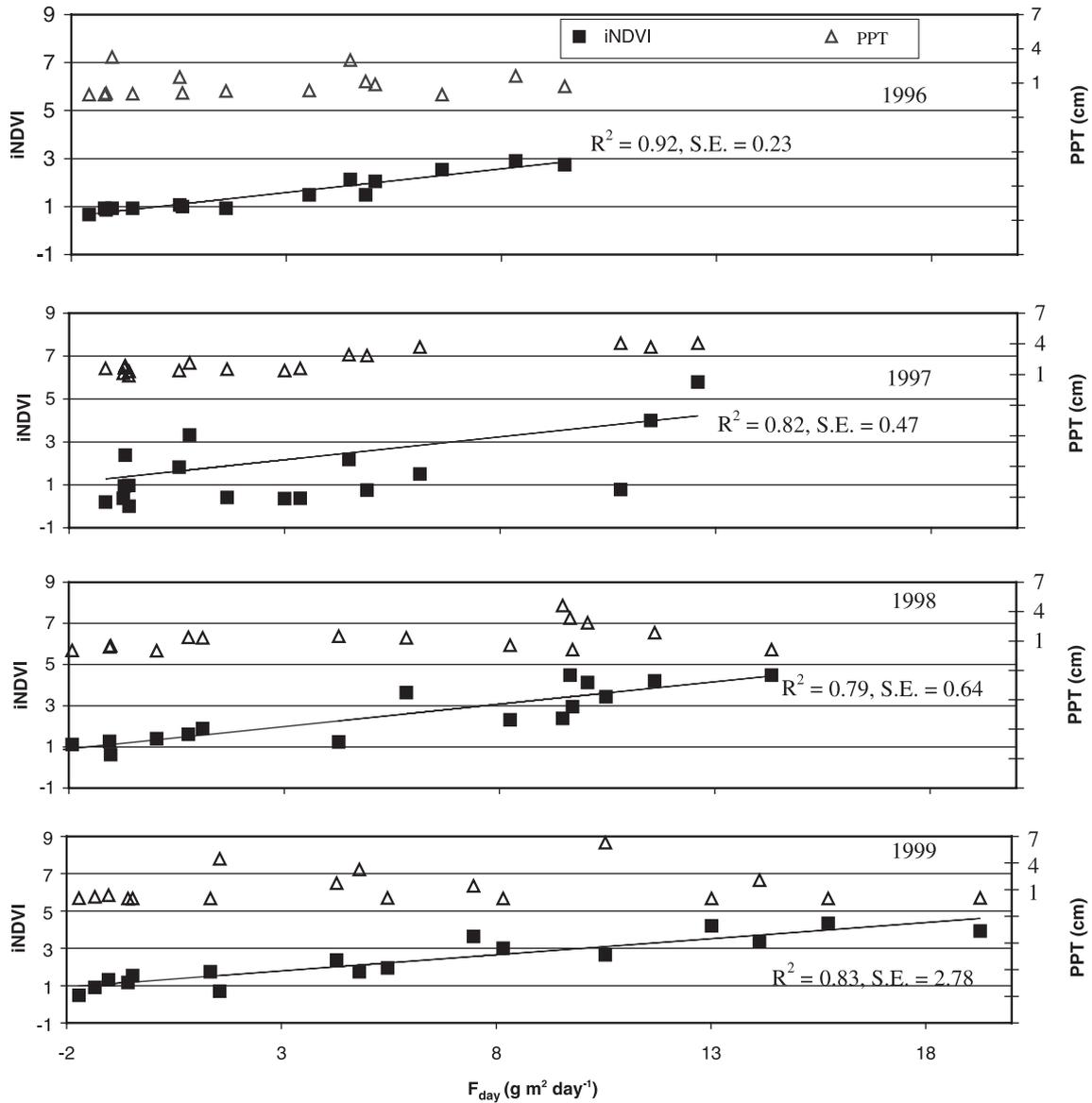
Fig. 2. Relationships between 14-day iNDVI, daytime CO_2 flux (F_{day}), and 14-day precipitation (PPT) for the 4 years of our study.

model. Inclusion of ET in the model may partially account for this phenomenon and possible variations in daytime R. Crossvalidation results (Table 2) indicated that both the

Table 2
Model statistics for biweekly regression and regression tree models used to estimate average 14-day diurnal CO_2 flux (F_{day}; g m^{-2} C) during the growing seasons of 1996–1999 ($n = 66$)

Model	R^2	R^2 autocorrelation[a]	R^2 crossvalidation	R^2 1999[b]
NDVI	0.79	0.62	0.79	
NDVI, ET[c]	0.82	0.69	0.81	0.88
Regression tree[d]	0.85		0.77	

[a] Temporal autocorrelation significant ($P < 0.01$) and corrected for.
[b] Accounts for 1999 significantly different slopes and intercept coefficients with indicator and interaction terms.
[c] Multicollinearity not a concern with a condition number of 8 < 30 (Freund & Littell, 1995).
[d] Not tested for temporal autocorrelation.

simple iNDVI model and the iNDVI-ET model performed similarly. Because these relationships were developed for only one location, these relationships need to be examined and tested at other locations.

If several flux towers were to be operated across several years in the same ecosystem across the landscape, confidence in the representativeness of the training samples to the population would increase and should improve the robustness of spatial predictions. The target population, however, would necessarily be spatially constrained by the ecoregion boundary and the particular land cover at the measurement site. Resulting spatial and temporal predictions would allow monitoring and assessment of arid and semiarid rangeland ecosystems where the spatial and temporal variation of both rainfall and plant production can be high. Comparisons with other predictions of NEE and photosynthesis (Cohen & Justice, 1999) could identify areas that require ground
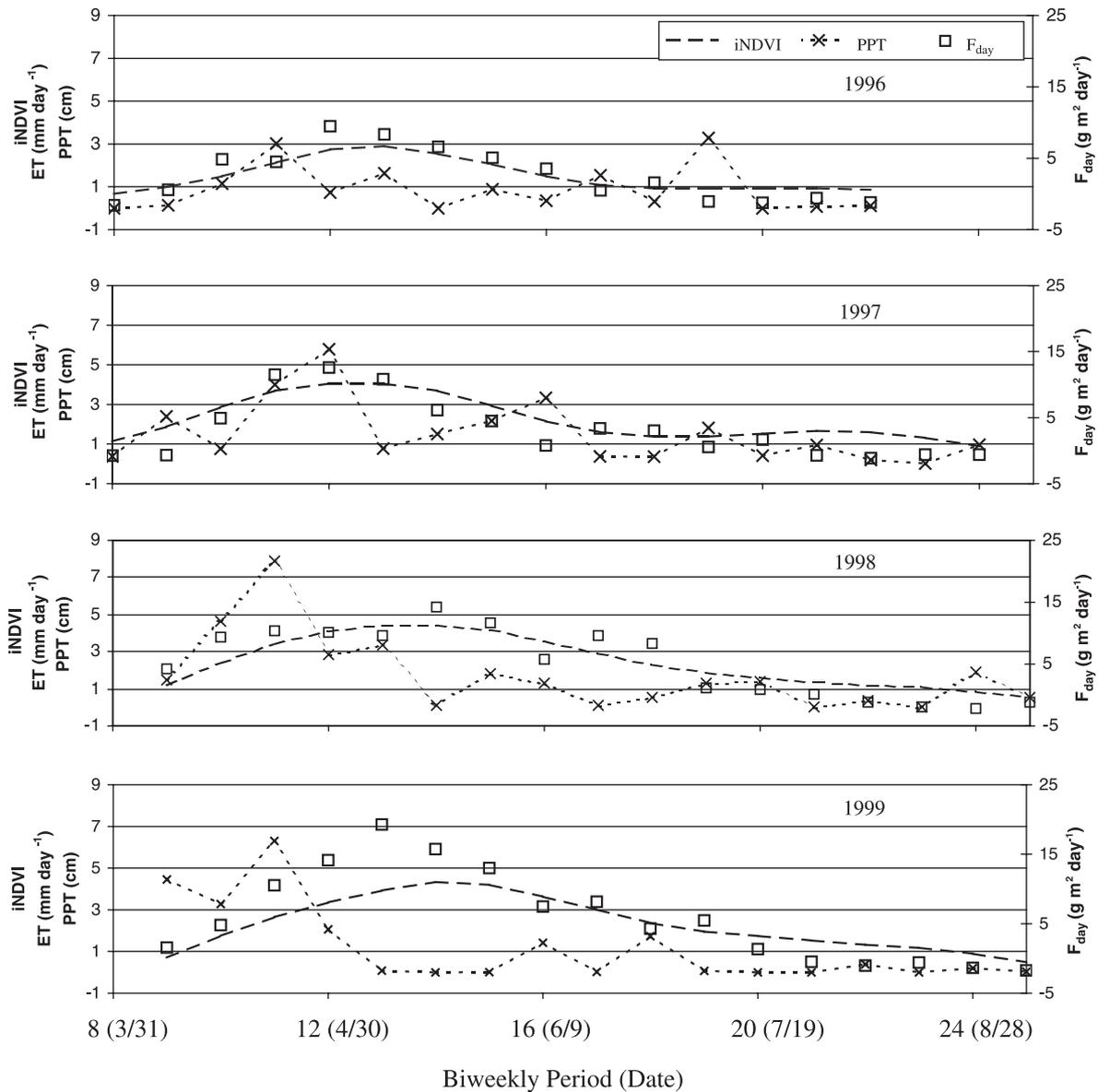
Fig. 3. Seasonal trends of 14-day iNDVI, evapotranspiration (ET), daytime CO_2 flux (F_{day}), and precipitation (PPT) for the 4 years of our study.

validation or further investigation. Inclusion of MODIS spatial and temporal estimates of LAI and fPAR could further improve CO_2 flux predictions, but such estimates are only available beginning in 2000.

Regression tree analysis was used to produce a regression tree model with a slightly higher R^2 value (0.85; Table 2). Crossvalidation with the regression tree analysis had a lower R^2 value (0.77), indicating that the regression tree model may have had some overfitting, which reduced robustness. Regression tree models perform better than linear regressions on large data sets that exhibit complex, nonlinear relationships and have interaction effects (De'ath & Fabricius, 2000). In this case, a strong overall linear relationship existed in the data.

These results indicated that iNDVI provided useful prediction information about the Dubois site, which was

improved with the inclusion of ET in the model. The addition of meteorological variables should allow refinement of the iNDVI and F_{day} relationship to reflect variations of RUE and daytime respiration. At this site, about 79% of the variation in F_{day} was explained by iNDVI. Remote sensing may complement gap-filling techniques for F_{day} when data gaps span large time frames, or where other techniques may be forced to extrapolate rather than interpolate. These algorithms also could provide estimates for other sites with similar characteristics.

4.2. Nighttime CO_2 flux (R_n)

Similar analyses were conducted to estimate R_n (Table 3). None of the R_n regression models had significant year effects. ET was the best single predictor of R_n, which

Table 3
Model statistics for biweekly regression and regression tree models estimating average 14-day nighttime CO_2 flux (R_n; g m^{-2} C) for the growing seasons of 1996–1999 ($n = 66$)

Model	R^2	R^2 autocorrelation[a]	R^2 crossvalidation
ET	0.53	0.46	0.52
ET, PPT, TAIR, VPD, WINDS	0.75[b]		0.66
Regression tree[c]	0.77		0.71

[a] Temporal autocorrelation significant ($P < 0.01$) and corrected for.
[b] Multicollinearity not a concern with a condition number of $8 < 30$ (Freund & Littell, 1995).
[c] Not tested for temporal autocorrelation.

Table 4
Regression tree variables used to stratify and predict average 14-day nighttime CO_2 flux (R_n; g m^2 C)

Variables	Stratification (% utilization)	Prediction weight
NR	0	0.9
PAR	0	0.9
SOILW	0	0.5
VPD	0	0.5
ET	100	0.4
TAIR	0	0.3
WINDS	0	0.3
iNDVI	0	0.2

outperformed iNDVI ($R^2 = 0.34$) and accounted for about half the variability in R_n. Similar R^2 values for the overall model and the crossvalidation modeling indicated this model was reasonably robust. Actual ET measured by the flux tower (ET) consists of evaporation and plant transpiration components. In this sagebrush–steppe ecosystem, ET was more strongly associated with iNDVI, NR, and PAR ($R^2 = 0.74$, 0.74, and 0.62) than air temperature (TAIR) and vapor pressure deficit VPD ($R^2 = 0.44$ and 0.19). The transpiration component of ET is likely more significant than the evaporation component in this ecosystem because iNDVI, net radiation (NR), and PAR are related to photosynthesis. This supports observed relationships with live-canopy biomass and R observed in rangelands of Inner Mongolia (Li et al., 2002).

The multiple regression relationship accounted for 75% of the variation in R_n, and crossvalidation indicated that this relationship was robust (Table 3). The selected independent variables in Table 3 were listed in order of relevancy with ET being the most relevant. Temperature has an important impact on R_n and was the third most relevant variable. However, there was no simple linear or nonlinear relationship between TAIR and R_n ($R^2 = 0.12$). Moisture availability was important for soil respiration processes. The variables in the multiple regression analysis that were related to soil moisture were PPT, VPD, and ET. The least relevant variable, WINDS, plays an important role in CO_2 fluxes affecting fetch area and mixing effects between the soil and atmosphere.

The regression tree model used only ET for stratification and eight variables to predict R_n (Table 4). The two most consistently used, highly relevant variables were associated with light availability (NR and PAR) followed by several variables associated with moisture [soil water content (SOILW) and VPD]. PPT, which was used in the multiple regression, was not used by the regression tree, and iNDVI was only slightly used. Crossvalidation indicated that regression tree models would have better prediction accuracies on withheld test data from this site ($R^2 = 0.71$; Table 3). Prediction of R_n was more complex than prediction of F_{day}, and the lack of a strong overall linear relationship resulted in the regression tree models having the best predictability. These techniques for estimating F_{day} and R_n, if developed from

multiple sites and years, would allow large area mapping of the seasonal dynamics of F_{day} and R_n. In addition, large area assessment of F_{net} could allow the monitoring of CO_2 fluxes that incorporate spatial and temporal dynamics present in arid and semiarid rangeland ecosystems.

4.3. Mobile tower simulation

If periodic rather than continuous measurements of F_{day} could be used in combination with iNDVI data to accurately predict CO_2 fluxes, then it may be possible to collect F_{day} and R_n flux data across multiple sites with a single mobile flux tower. This might improve the accuracy of both mechanistic and statistical models that estimate F_{day}, R_n, or NEE. Mobile towers also might allow an assessment of CO_2 fluxes and, in combination with remote sensing, may better account for temporal variations in CO_2 fluxes and thereby provide more accurate assessments of F_{day} across landscape or regional levels. Such an approach may allow a single flux tower to accurately monitor CO_2 fluxes at several sites, maximizing the utility of expensive flux towers. This may allow evaluations of different management treatments, carbon certification at several sites, and more effective parameterization and validation of CO_2 flux models.

Regression coefficients were quite stable across all three sequence periods for the simple regression between F_{day} and iNDVI (Table 5). Temporal autocorrelation was not significant ($P < 0.05$) in any of the sequence regressions. Most variability occurred in the slope coefficient, and the confidence interval for all observations overlapped the slope estimates for the three sequence periods. This and the magnitudes of the standard errors of the regression indicated that reasonably accurate and unbiased estimates of F_{day}

Table 5
Model statistics for the three time sequences and all observations pooled for daytime CO_2 flux (F_{day}) regressed on iNDVI

Sequence	Intercept	S.E.	Slope	S.E.	R^2	S.E. regression
1	−4.06	1.07	3.76	0.43	0.79	2.38
2	−4.80	1.00	4.34	0.41	0.85	2.24
3	−4.16	1.26	4.01	0.52	0.75	2.83
All	−4.34	0.63	4.04	0.26	0.79	2.44

Table 6
Multiple regression parameters for estimating daytime CO_2 flux (F_{day}) from iNDVI and evapotranspiration (ET) for three time sequences and all observations pooled

Sequence	Intercept	Slope NDVI	Slope ET	R^2	S.E. regression
1[a]	−3.90	3.23	0.51	0.79	2.41
2[a]	−4.28	2.70	1.56	0.89	1.93
3[a]	−3.76	2.23	1.84	0.80	2.61
All observations[b]	−3.93	2.96	1.01	0.86	2.06

[a] Autocorrelation not significant ($P < 0.01$).
[b] Corrected for first-order temporal autocorrelation.

would be obtained with iNDVI and periodic F_{day} measurements with a repeat cycle of every 6 weeks. Continuous flux measurements provided only a minor improvement in the standard error of the regression.

The parameters for the multiple regression relationships with iNDVI and ET were also robust across the three sequence periods, and regression coefficients for the individual sequence periods overlapped with those derived from all observations (Table 6). These results indicated that periodic measurements of F_{day}, as provided by mobile towers, could be used to accurately assess F_{day} with only minimal losses in flux information. Mobile flux measurements could also provide a spatial assessment of CO_2 fluxes by allowing three times the number of locations to be monitored with the same equipment.

5. Summary

Subdividing NEE or F_{net} into components of F_{day} and R_n allowed predictive models to be developed for both F_{day} and R_n. These component models for predicting F_{day} and R_n are more functionally based than a model for predicting NEE. Remotely sensed iNDVI alone or iNDVI, in combination with ET, was a strong predictor of biweekly values of F_{day}. This suggests that iNDVI is an important driver to consider for regional mapping of F_{day} CO_2 fluxes. Regression tree models provided robust predictions of R_n. Combining estimates of F_{day} and R_n may be useful in accounting for both temporal and spatial effects on carbon source and sink relationships in highly variable arid and semiarid rangeland ecosystems. This mapping also would be useful in determining the necessary timing and locations for monitoring various management scenarios for carbon sequestration. Mobile rather than stationary flux towers may allow a better spatial representation of regional CO_2 fluxes and facilitate spatial extrapolation of fluxes with minimal loss of accuracy from site-specific flux measurements.

Acknowledgements

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