

# Evaluating the Impacts of Thermal Sensor Revisit Interval on Remote Estimates of Evapotranspiration at Field Scales

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## Introduction

Since it is a fundamental linkage between many biogeophysical and biogeochemical processes, accurate spatially-distributed information regarding evapotranspiration (ET) is critical for a broad range of scientific and practical applications. Remote sensing-based approaches are the only viable mean for monitoring ET over the continuum from field to continental scales. Nonetheless, remote sensing is not without limitations. Chief among these is the infrequent acquisition of the medium to high-resolution imagery needed to determine ET via remote sensing-based models; this issue is further exacerbated by other factors such as cloud cover and instrumentation failure. A number of temporal scaling methods have been developed to fill the gaps in ET estimates between retrievals (e.g. Jackson et al. 1983; Colaizzi et al. 2006; Delogu et al. 2012; Ryu et al. 2012; Cammalleri et al. 2014).. These approaches typically estimate the moisture flux as the product of some reference quantity ( $\chi$ ) and its associate scaled quantity ( $f$ ) according to:

$$\hat{E}_t = \chi_t f_t \quad (1)$$

where  $\hat{E}$  is the estimated ET and  $t$  is the time period of the estimate. Typically the reference quantity is one that is closely related to the moisture flux but can be measured or modeled more accurately and readily than ET itself. The scaled quantity is the ratio between the reference quantity and the moisture flux. For example, it is quite common to estimate ET expressed in terms of the latent heat flux using the available energy as the reference quantity and evaporative fraction as the scaled quantity.

The aim of this project is to assess the error introduced into ET estimates by temporal upscaling under realistic conditions. Specifically, this project uses *in-situ* measurements collected over a variety of land cover types as proxy for remotely-sensed data to evaluate the impact of multiple reference quantities and interpolation techniques on the estimated moisture flux. By doing so, this study seeks to provide both insights into the relative strengths of the differing temporal upscaling approaches and discern a maximum return interval threshold for obtaining acceptable ET estimates.

## Methods

### *Datasets*

Datasets, including local meteorological conditions, surface fluxes, and surface conditions collected as a part of the Ameriflux network (Baldocchi et al., 2001) were used for this study. The data were collected at 20 Ameriflux sites (Table 1) distributed

across the contiguous United States representing four distinct land cover types: Cropland, Grassland, Forest, and Open Canopy. Measurements were collected for a minimum of five years at each of the sites selected.

After forcing closure of the energy balance while maintaining a constant Bowen ratio in order to more closely match the characteristics of model output, the 30-minute measurements were used to calculate the various reference quantities and scaled quantities. Finally, the daytime mean of these quantities were calculated for use in the subsequent analyses. Although it can nominally be taken as the period between 0800 and 1800 LST, daytime is defined herein as the period between the first and last measurements during the day when the incident solar radiation exceeded  $100 \text{ W m}^{-2}$ .

**Table 1** Summary of Ameriflux sites used in this study.

Site	Location	Land Cover	Site	Location	Land Cover	Site	Location	Land Cover
Bondville	40.006 °N 88.290 °W	Cropland	Kendall Grassland	31.737 °N 109.94 °W	Grassland	Missouri Ozarks	38.744 °N 92.200 °W	Forest
Brookings	44.345 °N 96.836 °W	Grassland	Konza Prairie	39.082 °N 96.560 °W	Grassland	Rosemount	44.714 °N 93.090 °W	Cropland
Brooks Field	41.692 °N 93.691 °W	Cropland	Loblolly Pine	35.978 °N 79.094 °W	Forest	Santa Rita Mesquite	31.821 °N 110.87 °W	Open Canopy
Chestnut Ridge	35.931 °N 84.332 °W	Forest	Lucky Hills	31.744 °N 110.052 °W	Open Canopy	Tonzi Ranch	38.432 °N 120.97 °W	Open Canopy
Fermi Cropland	41.859 °N 88.223 °W	Cropland	Mead	41.165 °N 96.477 °W	Cropland	Vaira Ranch	38.407 °N 120.91 °W	Grassland
Fermi Grassland	41.841 °N 88.241 °W	Grassland	Morgan Monroe	39.323 °N 86.413 °W	Forest	Walker Branch	35.959 °N 84.287 °W	Forest
Freeman Ranch	29.950 °N 97.996 °W	Open Canopy	Niwot Ridge	40.033 °N 105.54 °W	Forest			

### Reference Quantities

For this study, five reference quantities and their associated scaled quantities discussed in the literature were evaluated. The first three of these reference quantities, namely incident solar radiation ( $K_{\downarrow}$ ), net radiation ( $R_n$ ), and available energy ( $A$ ), yield direct analogues of evaporative fraction. The remaining reference quantities are estimates of the moisture flux derived using local meteorological conditions. The first of these is the so-called reference ET expressed in terms of energy ( $\lambda E_0$ ) and is defined according to Allen et al. (1998) as:

$$\lambda E_0 = \lambda_v \frac{a\Delta A + \gamma \frac{C_n}{T_K} UD}{\Delta + \gamma(1+UC_d)} \quad (2)$$

where  $\lambda_v$  is the latent heat of vaporization ( $\text{J kg}^{-1}$ ),  $a$  is a constant ( $1.1333 \times 10^{-4} \text{ kg J}^{-1}$ ),  $\Delta$  is the slope of the saturation vapor pressure-temperature curve ( $\text{kPa K}^{-1}$ ),  $A$  is the available energy ( $\text{W m}^{-2}$ ),  $\gamma$  is the psychrometric constant ( $\text{kPa K}^{-1}$ ),  $C_n$  is a constant ( $1.1333 \times 10^{-5} \text{ K s}^2 \text{ m}^{-2}$ ),  $T_K$  is the air temperature (K),  $U$  is the wind speed ( $\text{m s}^{-1}$ ),  $D$  is the water vapor pressure deficit (kPa), and  $C_d$  is a constant ( $0.25 \text{ s m}^{-1}$ ). The second of the

meteorologically-based reference quantities is the equilibrium latent heat flux ( $\lambda E_{eq}$ ). It is defined as:

$$\lambda E_{eq} = A \frac{\Delta}{\Delta + \gamma} \quad (3)$$

with the variables defined as above.

### *Interpolation Techniques*

In addition to a simple linear interpolation, two piecewise spline interpolation methods were evaluated as a part of this study, namely cubic and hermite spline interpolation. In contrast linear interpolation, which tends to yield accurate results only when the underlying data varies smoothly over time, the spline methods are less prone to error when the observed data varies abruptly. Similarly, the computationally more complex hermite spline method typically yields more accurate results when the gaps between observed data points are large (DeBoor, 1994).

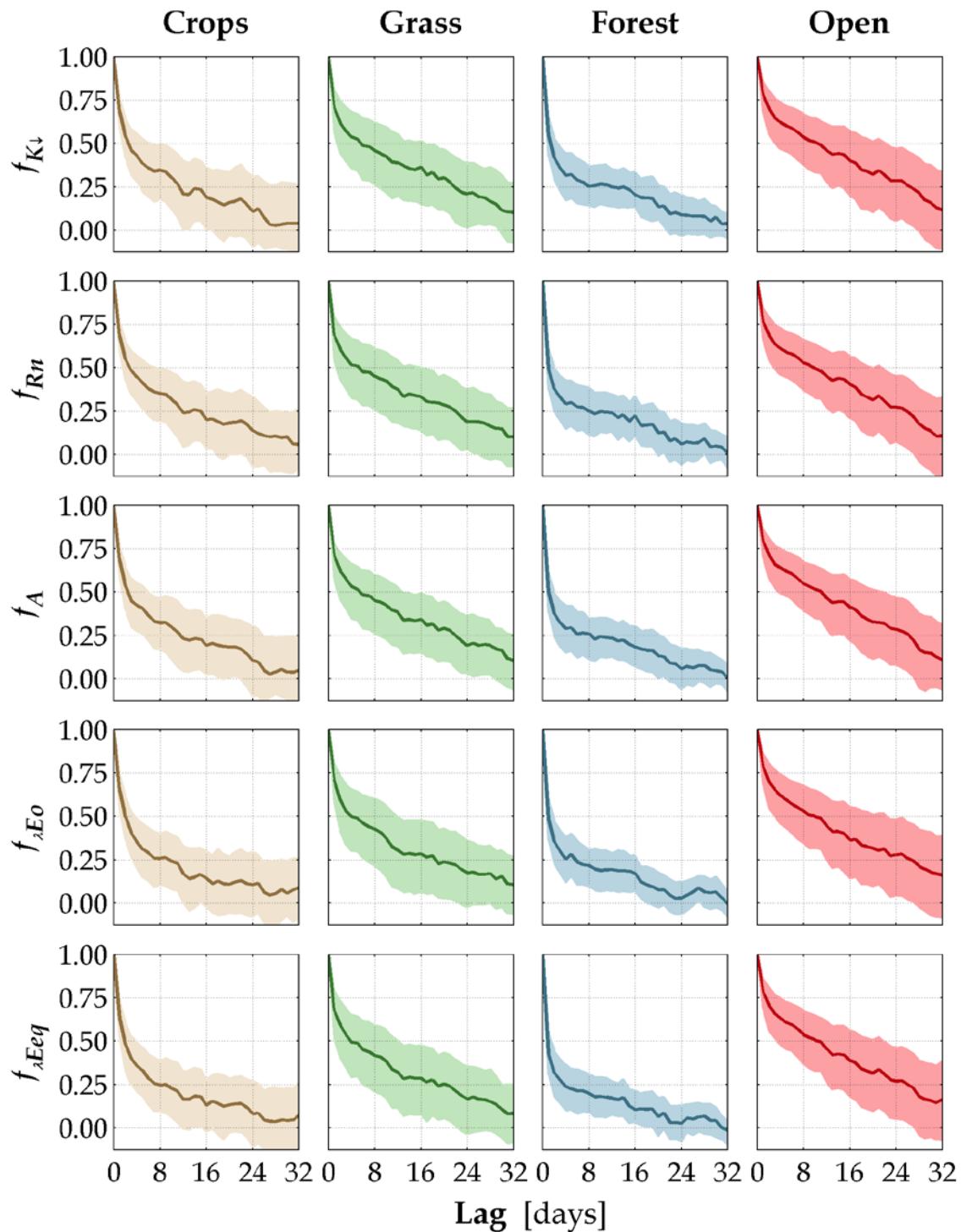
For this analysis, the temporal upscaling was conducted using daytime mean data and all possible combinations of the scaled quantities and interpolation methods at each Ameriflux site. Moreover, in order to maximize the robustness of the statistical analysis, all possible realizations were evaluated. The total number of possible realizations for a given return interval is equal to the length (in days) of the return interval. The individual realizations were generated by performing the analysis beginning on the consecutive days.

## **Results & Discussion**

### *Persistence of the Scaled Quantities*

Due to its importance in determining the accuracy of the estimates, the persistence, *i.e.* degree of self-preservation, exhibited by the various scaled quantities was evaluated using its autocorrelation function. As can be seen in Figure 1, the autocorrelation decreases rapidly and in proportion to the inverse of the lag. In all cases, the autocorrelation is less than 0.75 for lags greater than one day. It falls below 0.5 for lags greater than 3 to 10 days. The results of this analysis, which concurs with results of other studies (Farah et al. 2004; Lu et al., 2013), indicates the scaled quantities are not persistent in the long term. It also suggests that interpolated values may not accurately reflect the actual values of the scaled quantities. As a result, this approach for temporal upscaling may have limited utility for predicting ET when the return interval is large.

There are additional patterns evident from Figure 1. For any given land cover type, the mean autocorrelation functions for the analogues of evaporative fraction were statistically indistinguishable from one another based on t-tests conducted at the 95% confidence level; similarly, no statistically significant difference between the mean autocorrelation functions associated with the reference and equilibrium moisture fluxes. There were, however, statistically significant differences between the two subsets with



**Figure 1** The mean autocorrelation function is shown for each land cover type and scaled quantity. The shaded area represents one standard deviation about the mean.

the scaled quantities that are analogues of evaporative fraction tending to be slightly more persistent than those derived meteorological data.

The analysis also shows that differences in the mean autocorrelation functions that depend on land cover type. Regardless of the scaled quantity considered, the mean autocorrelation function decreases most rapidly over forested sites and the most slowly over the open canopy sites. Indeed, if the lag where the mean autocorrelation function reaches some threshold value, *e.g.* 0.50, is plotted as a function as the mean daytime latent heat flux (Fig. 2), it can be seen that persistence decreases exponentially with the increasing flux. This suggests the return interval necessary to achieve accurate estimates of ET via temporal upscaling will be longer over relatively dry regions with a low moisture flux than over regions where ET is high.

#### *Accuracy of the Interpolated Scaled Quantities*

The root mean square error of the interpolated estimates of each of the scaled quantities was calculated for return intervals (gaps sizes) of up to 32 days. As can be seen in Figure 3, the root mean square error (RMSE) increased rapidly with increasing gap size regardless of the land cover type, scaled quantity, or interpolation method considered. In all cases, the RMSE, which increased according to a logarithmic function of return interval, reached 75% of its peak value within five days. These peak values varied with land cover type but typically ranged between 0.15 and 0.5 (neglecting the results using the cubic spline method). Although no well-defined relationship could be identified, the largest errors tended to be associated with those land cover types (Forest and Cropland) with the largest mean moisture flux.

The results also show all of the interpolation methods yielded similar results for short return intervals (less than eight days). In contrast, for longer return intervals, the RMSE of the estimates using the spline interpolation methods were greater than when linear interpolation is used. Moreover, the RMSE of the estimates tended to much noisier for the spline techniques, particularly the cubic spline method. These large errors, which are indicative of “overshoot” errors, were most pronounced for those land cover types that type also demonstrated the highest average ET.

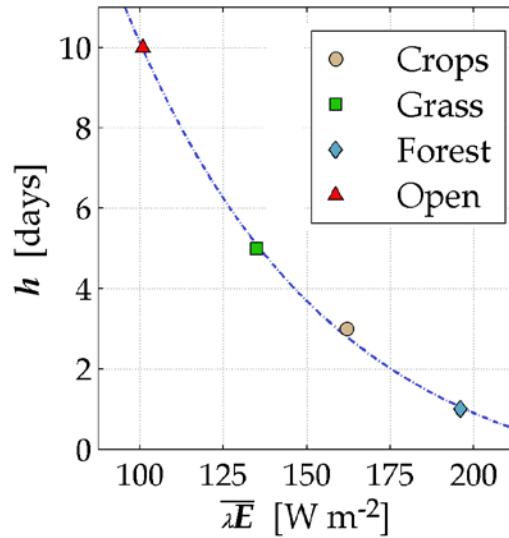
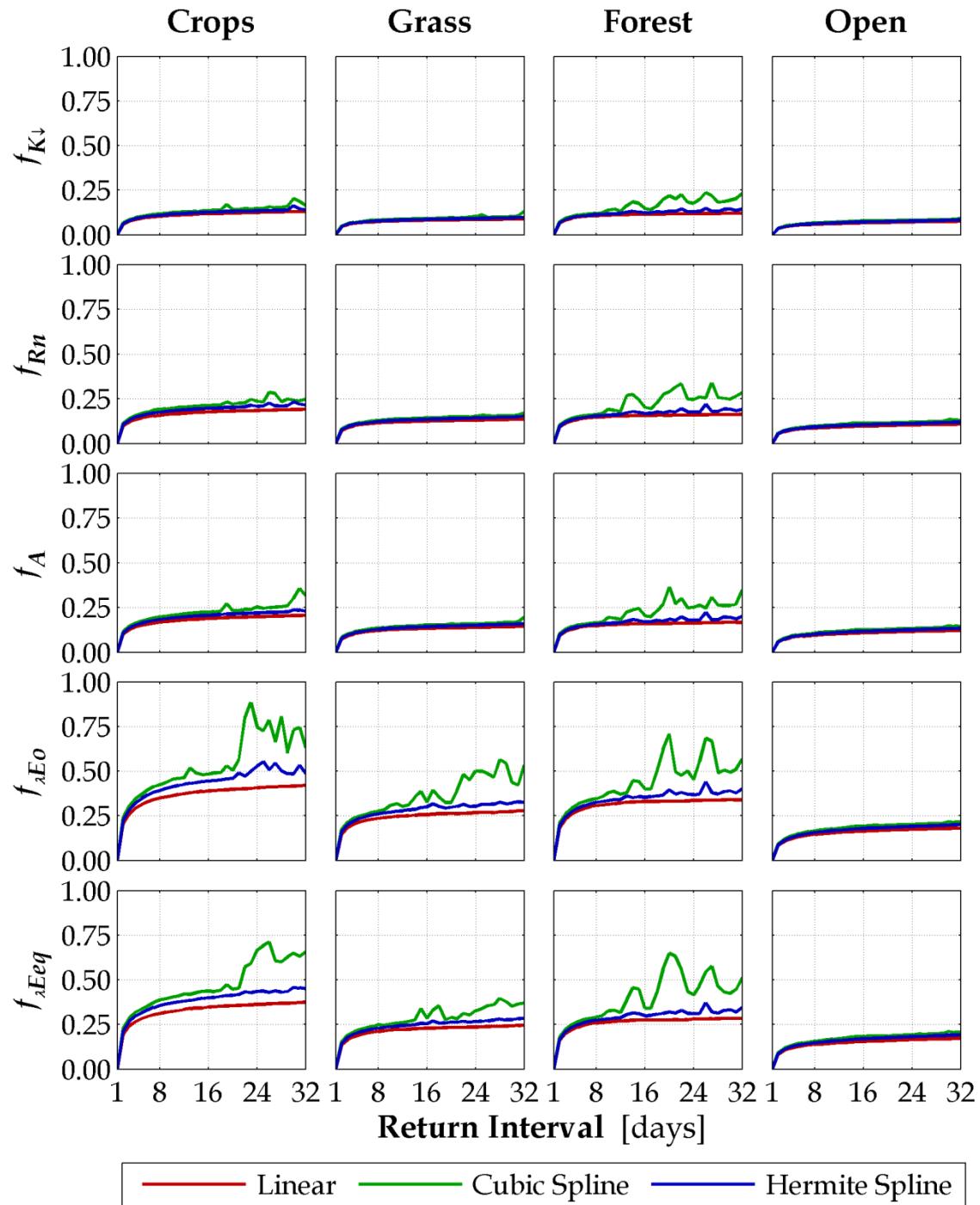


Figure 2 The maximum lag where the autocorrelation function exceeds 0.50 is plotted as a function of the mean daytime latent heat flux.

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**Figure 3** The root mean square error associated with each scaled quantity is shown for each land cover type and interpolation method.

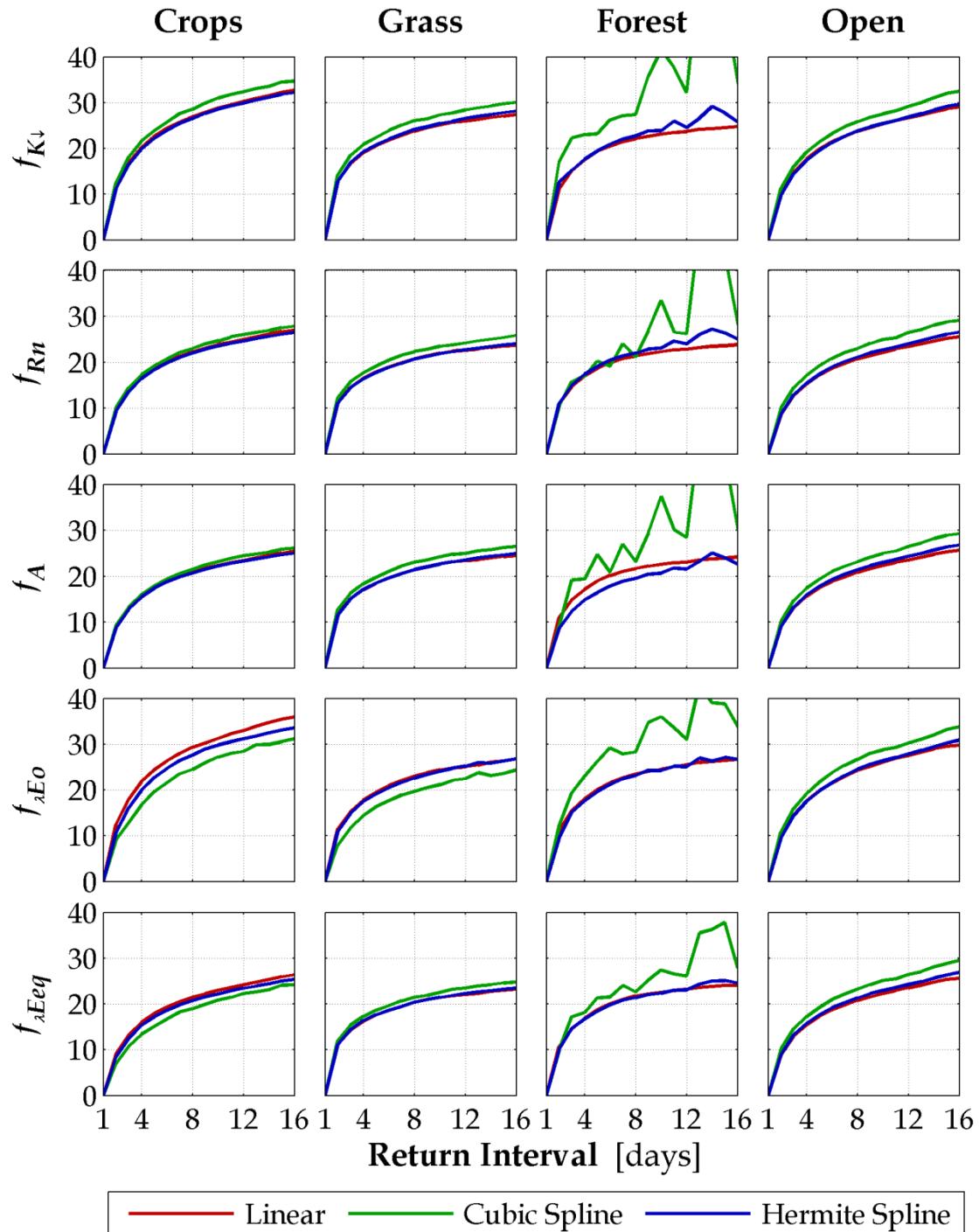
### *Accuracy of the Moisture Flux Estimates*

Not altogether unexpectedly, the accuracy of the moisture flux estimated via temporal upscaling closely paralleled the accuracy of the interpolated scaled quantities. Like the scaled quantities, the RMSE of the flux estimates increases rapidly with return interval to peak values ranging between  $31 \text{ W m}^{-2}$  and  $66 \text{ W m}^{-2}$ . Again, the greatest peak RMSE is associated with the land cover types with the highest ET, *i.e.* Forest and Cropland.

By expressing the error due to temporal upscaling as relative standard error (RSE), it is evident that the error approaches 40% within 16 days regardless of land cover, scaled quantity, or interpolation method (Fig. 4). Using 20% error as a threshold, the maximum return interval ranged between five and seven days with the sites having the lower mean latent heat flux (Grassland and Open Canopy) having the longer maximum return interval. It can also be seen from the figure that there is no advantage to using the computational complex cubic and linear spline methods. The cubic spline interpolation had a strong tendency to suffer from overshoot errors and there was no significant difference in the performance of the linear and hermite spline interpolation methods. Finally, the lowest RSE was consistently associated with net radiation while the greatest RSE tended to be associated with reference evapotranspiration.

### **Summary & Conclusions**

The persistence of all of the reference quantities considered decreased rapidly over time. For example, the lag necessary for autocorrelation to decease to 0.50 ranged between one and ten days with the lowest persistence associated with those land cover types with the highest mean ET. Similarly, regardless of the scaled quantity, land cover, or interpolation method, the error in the estimates of ET increased rapidly with return interval (gap size). Moreover, the error due to temporal upscaling was greatest over those land cover types with the highest ET. Using 20% error as the threshold, the maximum return interval ranged between five and seven days depending on land cover type. For a 10% threshold, the maximum return interval is approximately three day. This study also found that the scaled quantities that are analogous to evaporative fraction tended to those derived from meteorological conditions; net radiation yielded the ET estimates with the lowest error. Finally, the comparison of interpolation methods indicated there is no advantage to using the more computationally complex spline interpolation.



**Figure 4** The relative standard error associated with each scaled quantity is shown for each land cover type and interpolation method.

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