* **Results:**

The results from linear regression model (Flux ~ Rn + T + VPD + H + Season) supported our hypothesis that the rate of fluxes is primarily determined by net radiation (Rn), temperature (T), sensible heat (H), and Vapor pressure deficit (VPD) across seasons. We found that T had the largest impact (β = 0.0007073 ± 0.0001492, p < 0.0001), followed by Rn (β = 0.0005308 ± 0.0000084, p < 0.0001) and VPD with the least positive effect (β = 0.00001827 ± 0.0000019, p < 0.0001) on the fluxes. Interestingly, sensible heat flux (H) had a negative impact (β = -0.0004075 ± 0.000014, p < 0.0001) on the fluxes. On a seasonal scale, fluxes were higher (β = 0.0219 ± 0.00244, p < 0.0001) on summer compared to that in winter (β = -0.0167 ± 0.0025, p < 0.0001). However, the model only explained about 60% of the overall variability in the fluxes.

Exploratory data analyses showed a presence of non-linear trends towards higher end of the data values. Thus, to capture both linear and non-linear relationships among interrelated predictors and the response variable, a Generalized Additive Model (GAM) approach was used. The tensor smooth (te) basis function was used (Flux ~ Season + te(T, VPD, Rn, H, d = c(1,1,2))) to model the multidimensional interactions of variables that are not on the same scale. Similar to the results obtained in linear regression analyses, summer season had the largest (β = 0.0088 ± 0.0021, p < 0.0001) and winter had the lowest (β = -0.0117 ± 0.0022, p < 0.0001) impact on fluxes. The smooth terms were significant (p < 0.0001) with the model capturing approximately 78% of the variability in the dataset.

Furthermore, Akaike’s Information Criteria (AIC) model selection approach revealed that the tensor smooth model with cubic spline regression was the best fit model, given the data (Table 1). To test the model’s predictive performance, the dataset was split into training and testing datasets (80:20) and the model was allowed to predict on the testing data (data unseen by the model). The Root Mean Squared Error (RMSE) was found the least for the tensor smooth model (Table 1).

***Table 1.*** *Results of Akaike’s Information Criteria (AIC) approach for model selection.*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model** | **df** | **AIC** | **RMSE** | **R-squared** |
| Linear | 9 | -23388 | 0.00687 | 0.6213 |
| GAM additive | 35 | -25019 | 0.00605 | 0.6500 |
| GAM interactive | 95 | -26396 | 0.00541 | 0.6950 |
| GAM tensor smooth | 312 | -28195 | 0.00524 | 0.7780 |

Taken together, these model results suggested that the GAM better explains both the linear and non-linear relationships among predictors and the fluxes in this data. The model couldn’t explain roughly 20% of the variability in the data that can be attributed to other factors including additional drivers. These results can be improved by training the model with more data and including additional relevant predictors in the model architecture.