

S1 Potential correlation between SWC and VPD during periods of high VPD

In the analysis of the drivers of CO₂ fluxes, we controlled for correlations with TA and VPD, however especially the moisture-induced control via VPD or concurrent SWC limitations may provide another confounding effect influencing fluxes. We did not include SWC as a driver in the predictor selection process but only WT. Therefore, we additionally tested the correlation of VPD and SWC for each season. The Pearson correlation coefficient of the measured SWC and VPD was 0.12, -0.4 and 0.06 while for the anomalies they are -0.08, -0.21 and -0.03 in the NGS, EGS and LGS respectively. Correlations between SWC and VPD on the daily scale were thus low except for the early growing season, however working solely with anomalies also effectively reduced the correlation.

S2 The impact of gap-filled data on driver analyses done on daily aggregated flux time series

Driver analyses on EC derived fluxes are often done on the daily scale (Krebs et al., 2025; Scapucci et al., 2024; Shekhar et al., 2023), as on the sub-daily scale the fast responses to the daily cycles of radiation and temperature vastly dominate the signal. However, aggregating the data to the daily scale results almost inevitably in the inclusion of modelled data in the daily means. Half-hourly fluxes are filtered for a range of reasons, most prominently for periods of poorly developed turbulence. In our data of three years only 178 days contain no filled datapoints. Further, not including any filtered data may result in a selective and skewed data bias as such poorly developed turbulence conditions develop under specific climate conditions (during temperature inversions, at night etc.). Nevertheless, including modelled data in a driver analysis bears the risk of introducing circularity, as effects strengths of drivers are derived from data modelled with said drivers. We introduced a threshold of maximum allowed inclusion of gapfilled data of 50%. This is assumed to reduce the weight of the modelled data as well as remove any data in large gaps, as model uncertainty is known to increase within longer gaps (Lucas-Moffat et al., 2022; Vekuri et al., 2025)

To test the impact of modelled data on the driver analysis we repeated our analysis of the effect strength of climate anomalies on CO₂ fluxes for several thresholds of maximum allowed gapfilled data percentage per day, covering range of allowed percentages from 10 to 80%. Since this process introduces uncertainty through the data selection, we additionally bootstrapped the analysis, resampling the data 50 times for each threshold, allowing us to present the mean and standard deviations of the driver strengths.

The sign and magnitude of the effect strengths remained remarkably similar across a wide range of gapfilled percentages. Some drift occurs in the effect strengths starting at a threshold of 30% or lower (e.g. for NEE in the early growing season Fig. S1 a). Notably though, this threshold would already result in the removal of 483 of the 1096 days and likely introduce a biased filtering. Some concurrent drift in the effect strengths of z_{TA} and $z_{TA:Z_{SWIN}}$ can be observed for non-growing season GPP (Fig. S1 b) which however was poorly captured by the model ($R^2 = 0.32$ for the 50% threshold) and is expected to be mostly near zero (during full dormancy) or very dynamic during the transition to the growing season. A few selected predictors seemed to be sensitive to the threshold of gapfilled data percentage, especially appearing at very low percentages of gapfilled data (e.g. in the LGS for Reco, Fig. S1 c). As these are heavily subset datasets it is unclear whether they would adequately represent the respective seasonal periods.

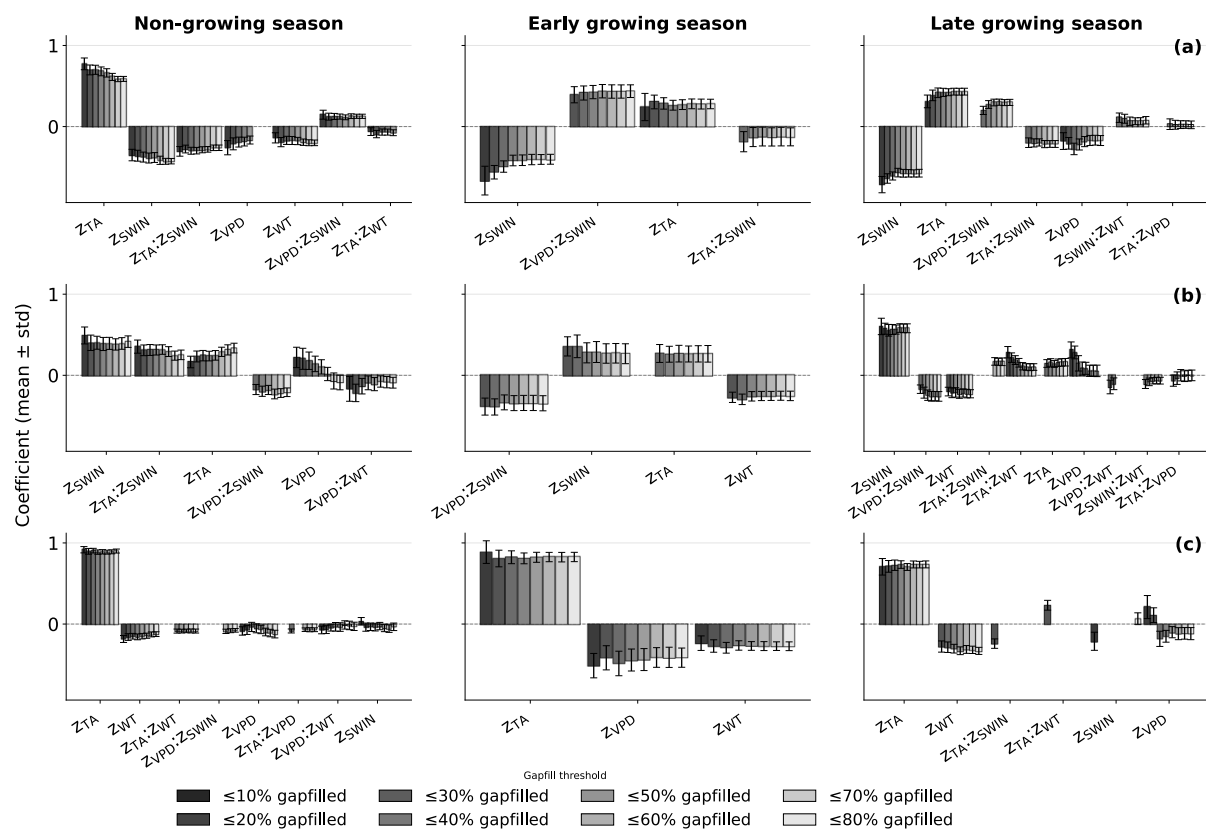


Figure S1: Effect strength of anomalies of different climate and hydrological variables and their inteactions on anomalies in NEE (a), GPP (b) and Reco (c). The analysis was done on the daily scale and repeated for different threshold of allowed percent of gapfilled data per day. Each model was bootstrapped 100 times to derive standard deviations of effect strengths, drivers were only included if they were selected in the model in at least 60% of the models.

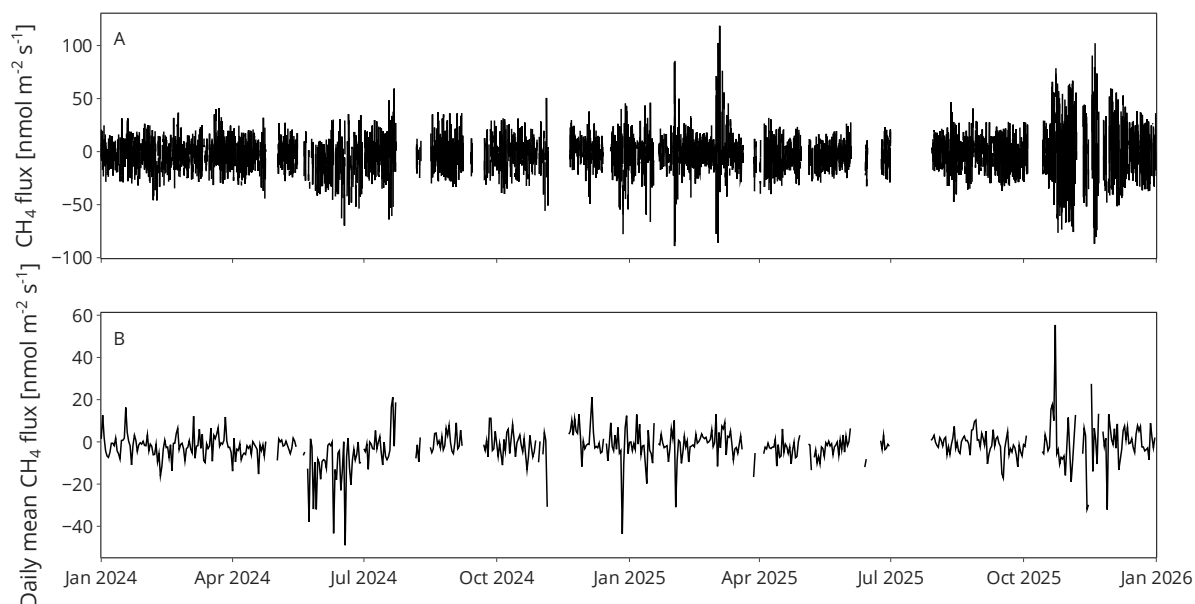


Figure S2: Unfilled, u^* -filtered and despiked time series of CH_4 flux over two years from Amtsvenn on the half-hourly scale (A) and the daily scale (B).

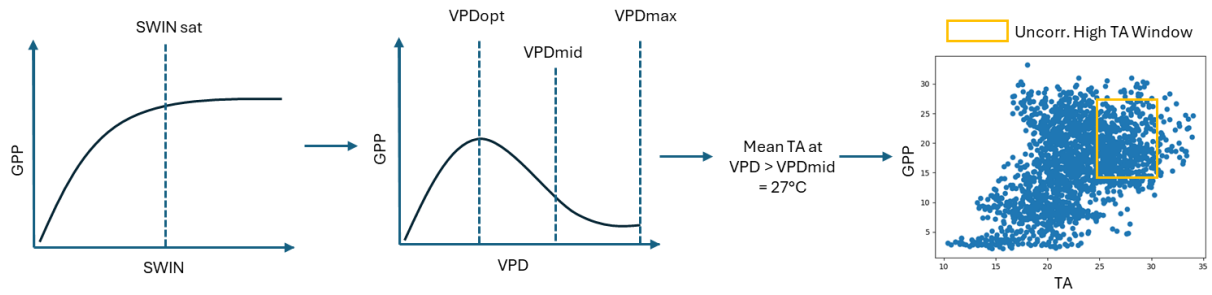


Figure S3: Conceptual flow chart of the procedure to evaluate the influence of VPD on fluxes while controlling for correlated effects of short-wave incoming radiation (SWIN) and air temperature (TA).

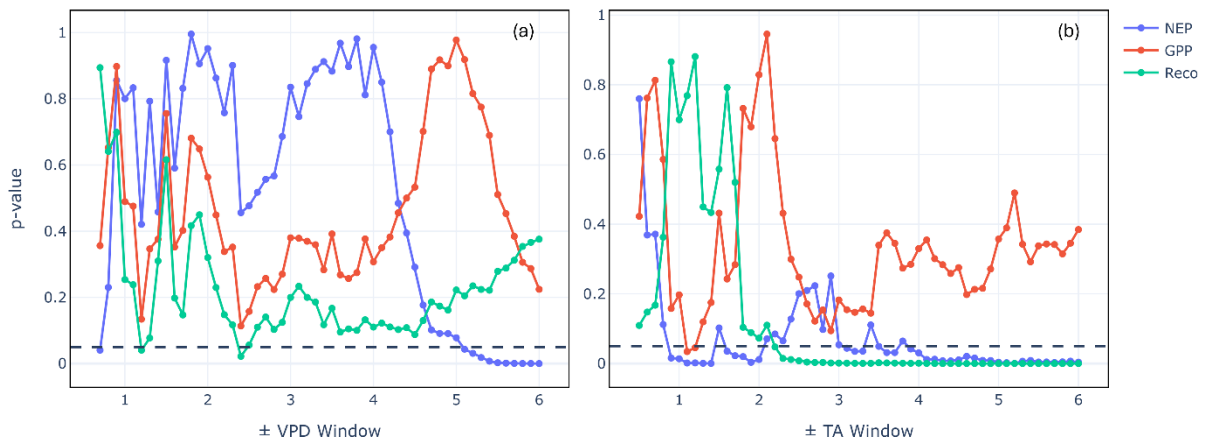


Figure S4: Sizes of the windows of VPD (a) and TA (b) around the chosen midpoint alongside p values for linear regression for the three variables NEE, GPP, and Reco with VPD or TA in that range. The dashed line denotes a p-value of 0.05.

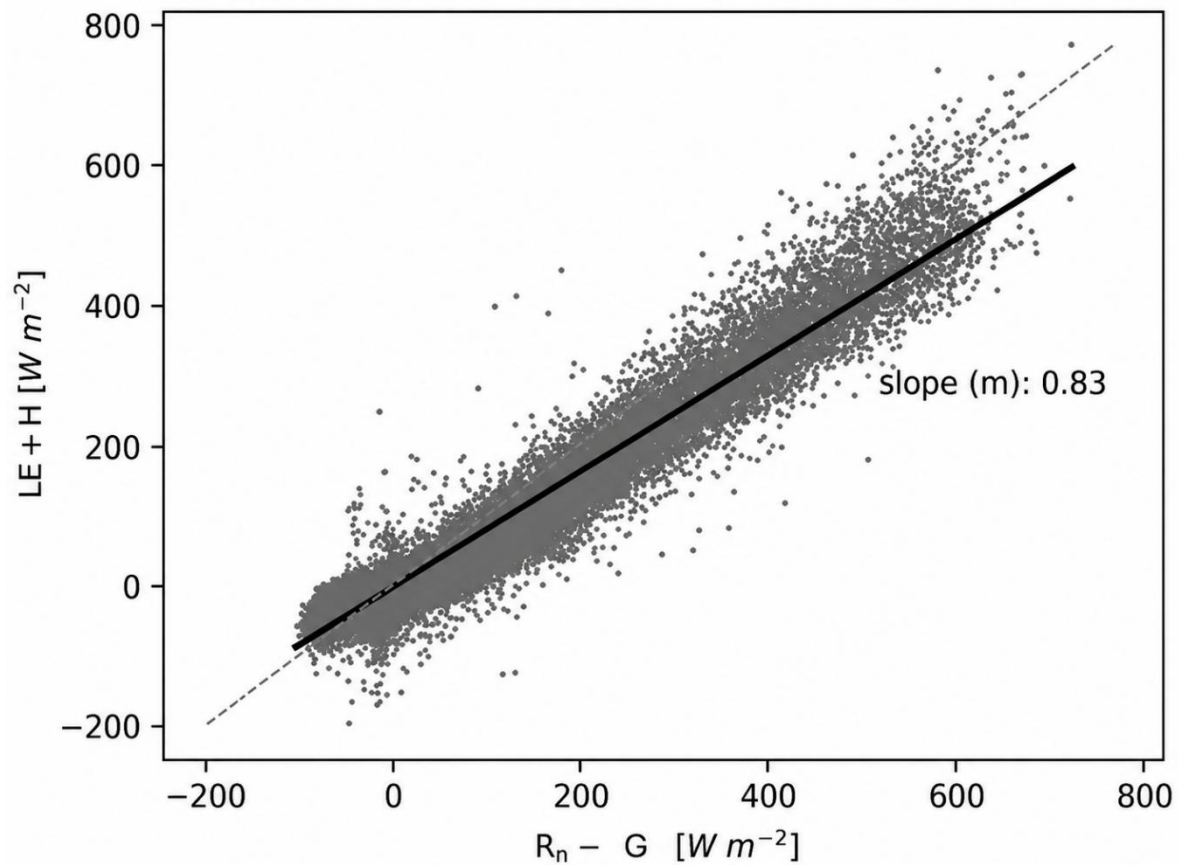


Figure S5: Energy balance closure determined by the slope between half-hourly measured and non-gap filled heat fluxes and radiation balance minus ground heat flux in DE-Amv, during the study period (2023–2025).

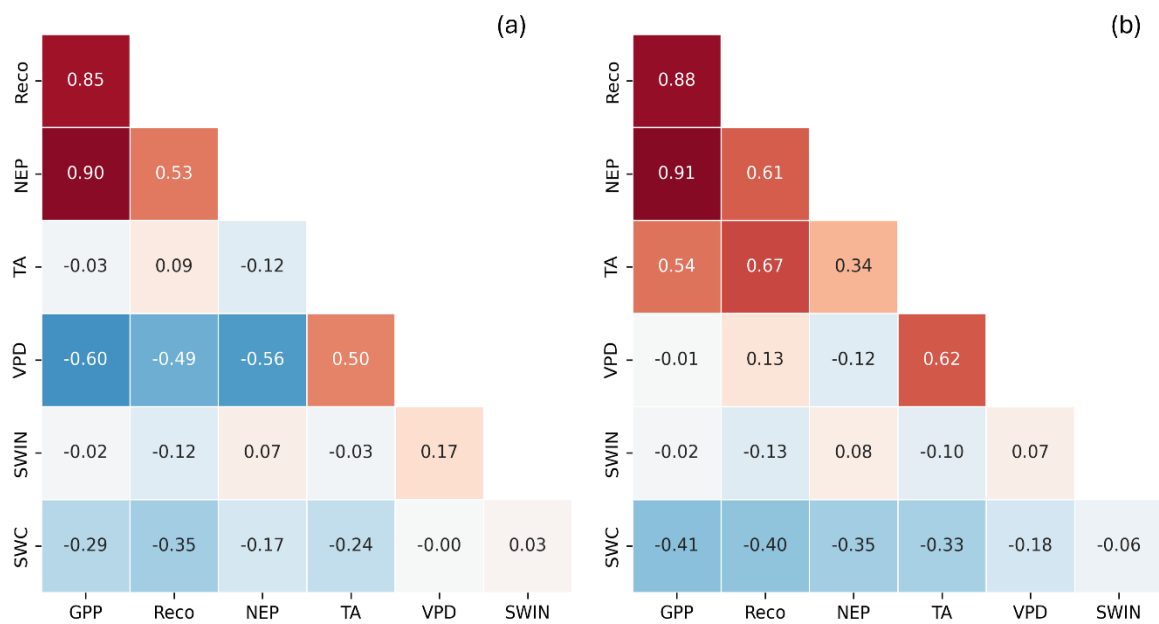


Figure S6: Correlation matrix of fluxes (GPP, Reco and NEP) and meteorological drivers SWC, TA, VPD and SWIN after the data was controlled to only include radiation saturated GPP data and was cleaned for VPD correlation (a) or TA correlation (b).

References

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