Supplementary material

Supplementary Text

Section 1. Scaling individual dendrometer measurements to the plot level
Tree height allometries were calculated for each site using the following equations.
(SM Eq. 1) Height = $\beta_0 + \beta_1$*DBH
(SM Eq. 2) Height = $\beta_0 + \beta_1$*log(DBH)
(SM Eq. 3) Height = β_0*[(1/wd)^β_1]*DBH^2
The model fit was compared by AIC, where the non-linear fit (SM Eq.3) was consistently the best fit. Then the predicted tree height, the wood density, and its diameter were used with equation 4 from Chave et al., (2016) to estimate the aboveground biomass. This was converted into carbon content with a dry biomass ratio of 47.8% for each tree.

Section 2. Meteorological predictors
We corroborated the accuracy of the TerraClimate product with downscaled monthly estimates produced by applying a machine learning regression technique to predict 3-hourly meteorological values from automatic weather stations located at or near the GEM sites used in this study. The actual meteorological observations from the weather stations were generally too short in time period (2 - 10 years of operation at each site). We could not use raw weather station observations for the NPP_{stem} statistical model fitting because of data gaps, owing to power failures and/or sensor failures in the weather stations.
ERA-Interim is a well established climate reanalysis product, however owing to the coarse 0.25 degree spatial resolution, the raw outputs do not well capture the micrometeorological environment of a forest plot. Thus a downscaling method was needed to align the ERA-Interim meteorological estimates to that of the local environments surrounding the forests plots.

However, while this downscaling method can gapfill and extend weather station records - it cannot fix intrinsic sensor errors or biases. For example, we believe the downscaled predictions for VPDmean from Ankasa (ANK) are flawed due to unrealistically high relative humidity values from the weather station sensor. The mismatch between the downscaled VPDmean estimates from the Malaysian Borneo and the TerraClimate estimates are likely caused by the downscaling method applied to the Maliau (MLA) and Danum (DAN) sites. Further, the SAFE weather station (SAF) is from an eddy flux tower that is only kilometers away from vast palm oil plantations. This transition in humidity may not be well characterized by the TerraClimate product, but we can not be sure at this time if the downscaling process was flawed by weather sensor errors or problems intrinsic to the ERA-Interim driver variables. The TerraClimate Tmean estimates are also meant to correspond to 2-meter high standard weather stations, whereas the SAFE eddy flux tower is well above the canopy, where the VPD will be higher.

We used a stochastic gradient boosting algorithm to predict each meteorological variable using the surface level diagnostic variables from the ERA-Interim climate reanalysis product as predictors. This enabled the site-level meteorological record to be extrapolated through time (and gap-filled where necessary) with considerably more accuracy than using the raw ERA-Interim estimates for temperature and vapour pressure deficit. ERA-Interim was chosen over other climate reanalysis products because it was found to be the most accurate of gridded climate products over tropical forest regions (Burton et al., *in press*). However we could not use ERA-Interim for surface level downwelling shortwave radiation due to a known error in the reanalysis model diagnostic writing process. Instead we used the MERRA2 climate reanalysis product [48], and the remote sensing based surface level shortwave estimates from the CERES EBAF product to examine monthly mean shortwave radiation. The mean monthly cloud fraction was also calculated from the long-term PATMOS-X product to corroborate the other estimates of shortwave radiation.

Precipitation related metrics at the plot level were derived from the CHIRPS v2.0 satellite rainfall product [49] sampled at 0.05° spatial resolution. Climatic water deficit (CWD) and a 12-month running maximum climatic water deficit (MCWD) were calculated as follows [29]:

(SM Eq. 4): $CWD_t = min(CWD_{t-1} + Precip_t + ET_t, 0)$

(SM Eq. 5): $MCWD_t = min(CWD_t \ldots CWD_{t-12})$

$Precip_t$ and ET_t are the precipitation and evapotranspiration of the month *t*. Monthly evapotranspiration estimates (ET_t) were derived by taking the 2002-2014 spatially varying monthly means from the MOD16A2c005 Net Evapotranspiration product [50] (SM Fig 1). Hence CWD provides an estimate of water stress, without accounting for local soil and water retention properties, which are often poorly described in the tropics and hence difficult to scale. We also use a simple metric to characterize the wet-dry seasons transitions (WDT) that is calculated as:

(SM Eq. 6): $WDT_t = Precip_t - mean(Precip_{t-1}, Precip_{t-2})$

Despite its simplicity the WDT metric largely captures the arrival of the wet season (positive WDT) and the transition to the dry season (negative WDT).

Section 3. Pantropical predictions of NPP_{stem}

Predictions were limited to 0.5° grid cells with at least 50 km^2 of forest cover (in 2016) using the Global Forest Cover product v1.4.

The CERES record of shortwave radiation begins in 2000. We applied a linear correction factor to the TerraClimate estimates of to better match the moving 3-month anomalies of shortwave radiation from the CERES estimate. The scaled TerraClimate shortwave anomaly estimates were then used to gapfill the CERES shortwave anomaly estimates when producing the NPP_{stem} predictions for the aseasonal wet tropical forest regions ($S < 0.05$). These aseasonal wet tropical regions, where the aseasonal wet forest was was applied are shown in SM Fig. 9. The range of mean annual precipitation, and temperature range from the GEM sites broadly covered most of the tropical forest regions (SM Fig. 9).

Supplementary Tables

SM Table 1. R2 with and without random effects (RE) are presented for the meteorological effects for the aseasonal wet forest data.

Seasonal Forest Model Terms	R2	R2 (no RE)
Intercept only	0.14	0
u_Tmean	0.17	0.03
u_Tmean + Tmean_anom	0.17	0.03
u_Tmean + Tmean_anom_3mo	0.17	0.03
u_VPDmean	0.35	0.19
u_VPDmean + VPDmean_anom	0.36	0.19
u_VPDmean + VPDmean_anom_3mo	0.35	0.19
u_SW	0.19	0.06
u_SW + SW_anom	0.21	0.08
u_SW + SW_anom_3mo	0.23	0.11
u_SW.ceres	0.13	0
u_SW.ceres + SW_anom.ceres	0.15	0.02
u_SW.ceres + SW_anom_3mo.ceres	0.24	0.06
u_cloud_fraction	0.36	0.2
u_cloud_fraction + cloud_fraction_anom	0.36	0.21
u_CWD	0.29	0.16
u_CWD + CWD_anom	0.29	0.17
u_MCWD	0.18	0.21
u_MCWD + MCWD_anom	0.18	0.2
u_water_deficit	0.43	0.27
u_water_deficit + deficit_anom	0.44	0.28
u_water_deficit + deficit_anom_12mo	0.43	0.28

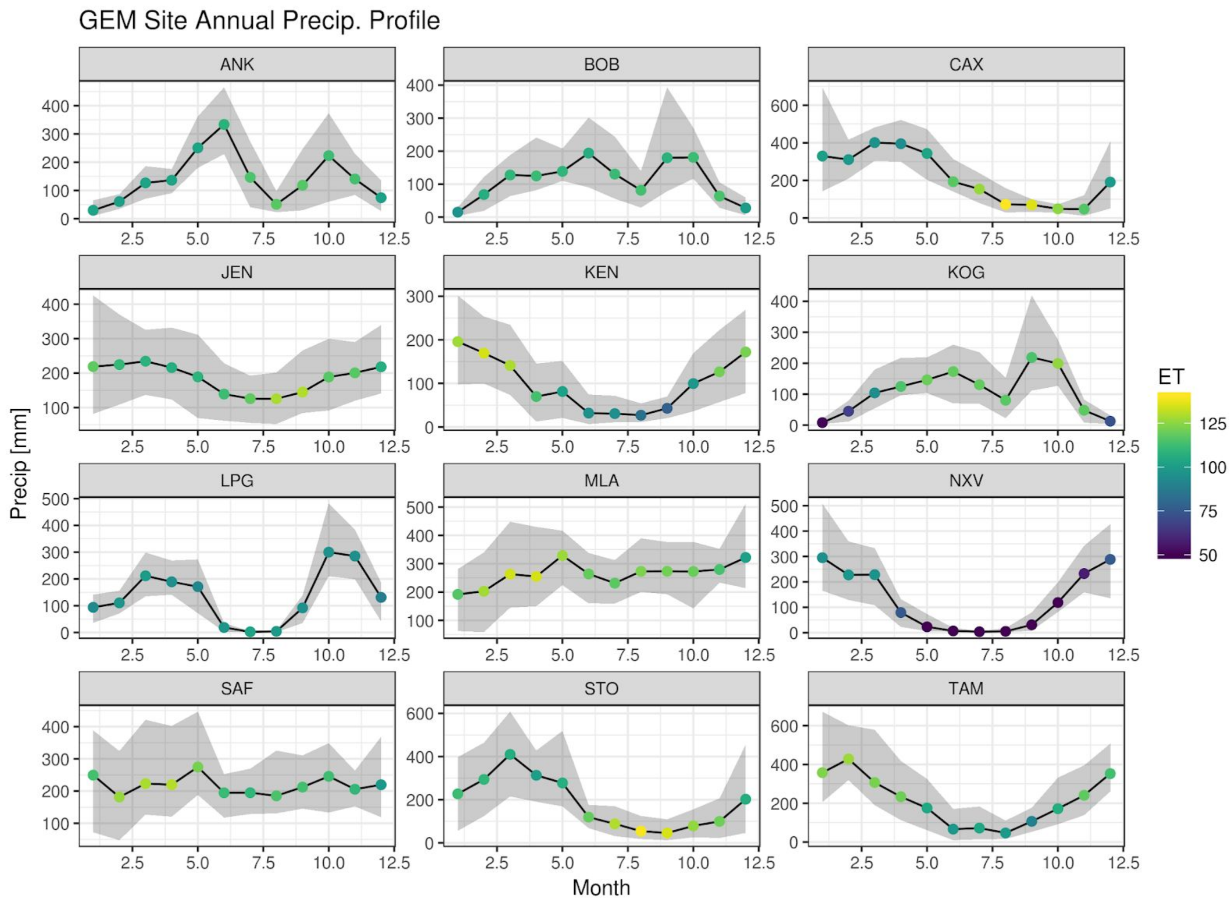
u_VPDmean + u_Tmean + u_SW + dry_anom_sigma + wet_anom_sigma + spline(sw_anom_sigma_3mo)	**0.52**	**0.35**

SM Table 2. R2 with and without random effects (RE) are presented for the meteorological effects for the aseasonal wet forest data.

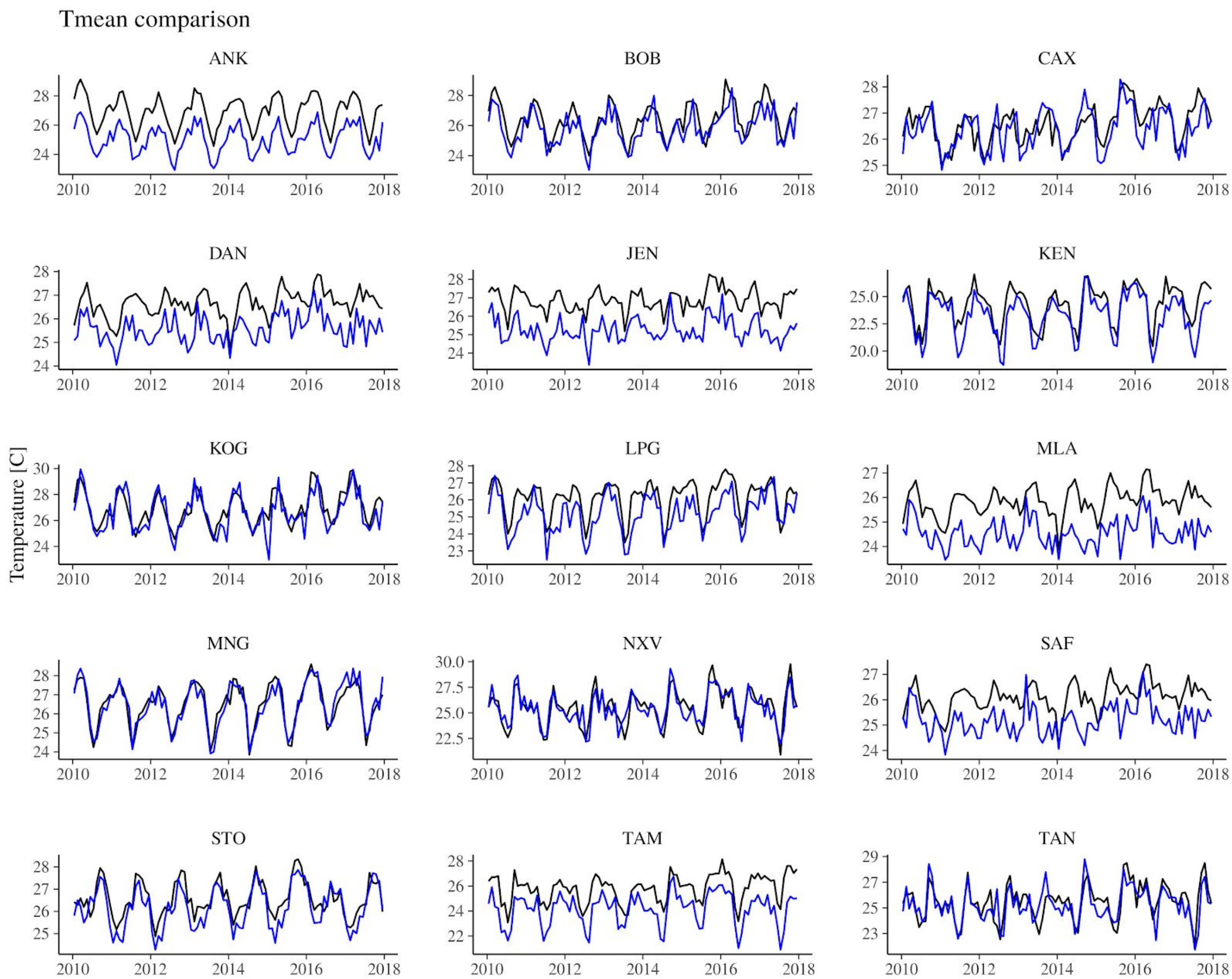
Aseasonal Wet Forest Model Terms	R2	R2 no RE
Intercept only	0.18	0
u_Tmean	0.19	0.01
u_Tmean + Tmean_anom	0.25	0.07
u_Tmean + Tmean_anom_3mo	0.24	0.06
u_VPDmean	0.2	0.01
u_VPDmean + VPDmean_anom	0.35	0.14
u_VPDmean + VPDmean_anom_3mo	0.4	0.18
u_SW	0.21	0.02
u_SW + SW_anom	0.22	0.04
u_SW + SW_anom_3mo	0.29	0.11
u_SW.ceres	0.21	0.02
u_SW.ceres + SW_anom.ceres	0.21	0.03
u_SW.ceres + SW_anom_3mo.ceres	0.24	0.06
u_cloud_fraction	0.22	0.4
u_cloud_fraction + cloud_fraction_anom	0.24	0.06
u_CWD	0.214	0.024
u_CWD + CWD_anom	0.22	0.036
u_MCWD	0.21	0.02
u_MCWD + MCWD_anom	0.25	0.06
u_water_deficit	0.21	0.02
u_water_deficit + deficit_anom	0.27	0.07
u_water_deficit + deficit_anom_12mo	0.26	0.06

VPDmean_anom_sigma_3mo + def_anom_sigma + sw_anom_sigma_3mo.ceres	**0.41**	**0.2**

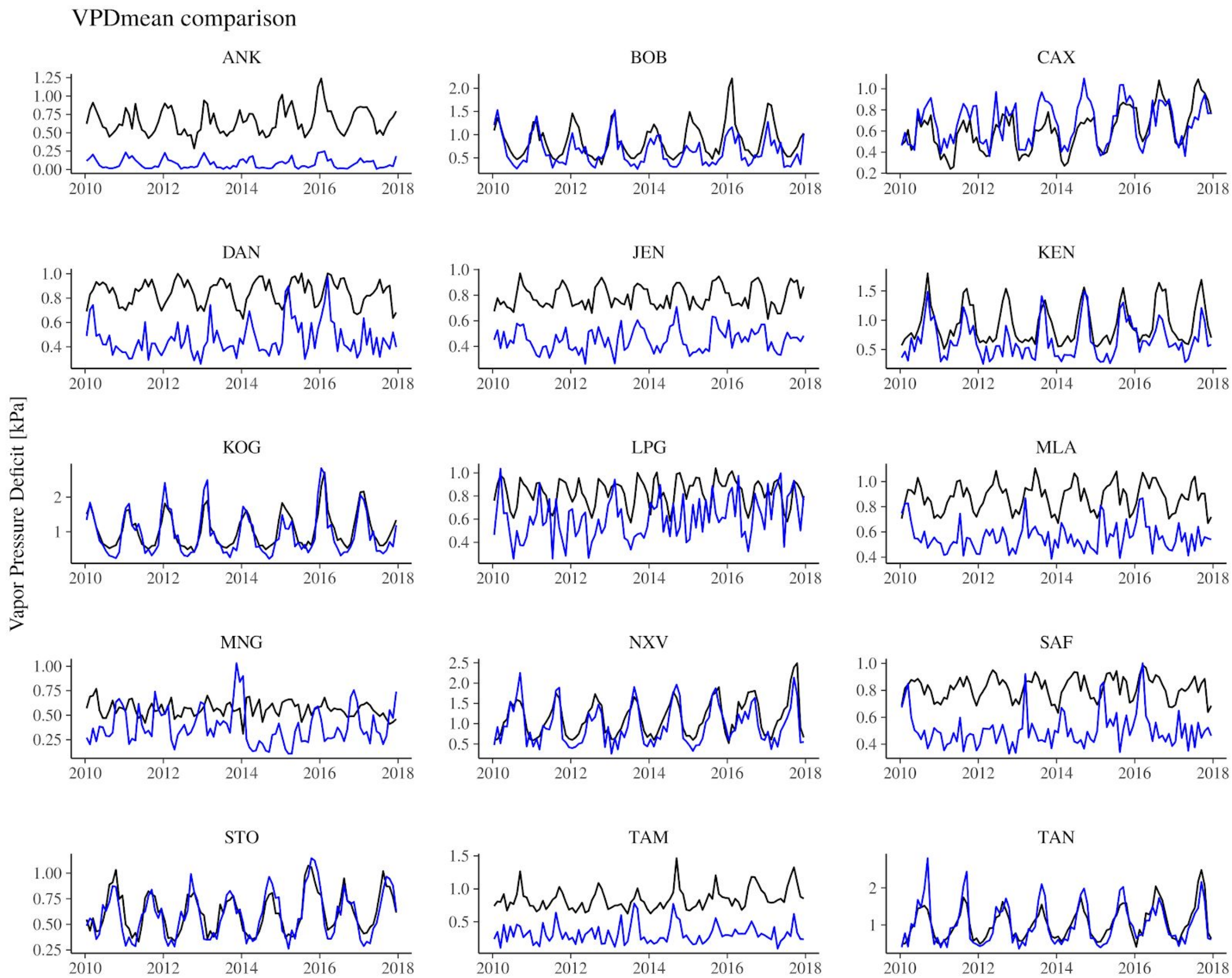
Supplementary Figures



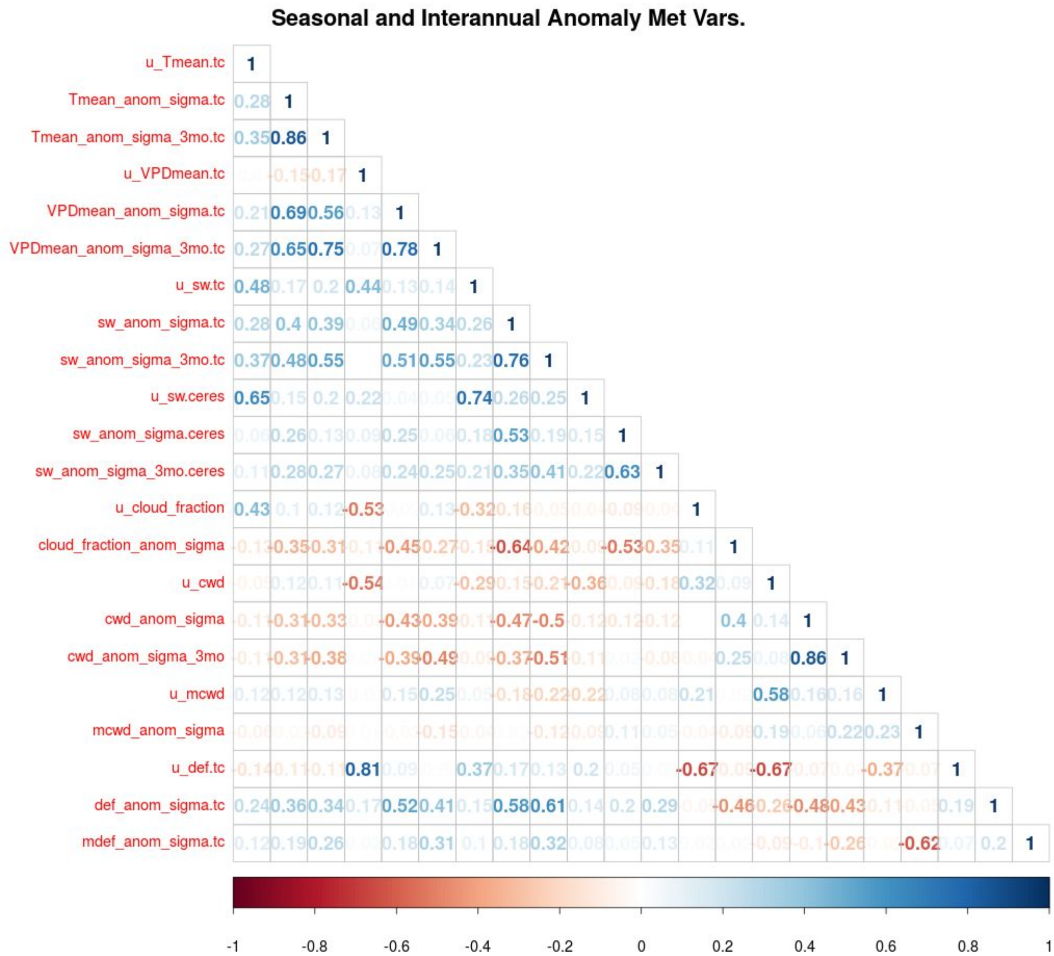
SM Figure 1. The 30 year median with 90% quantile of monthly rainfall. ET is the 14 year average from the MODIS MOD16A2.005 evapotranspiration product.



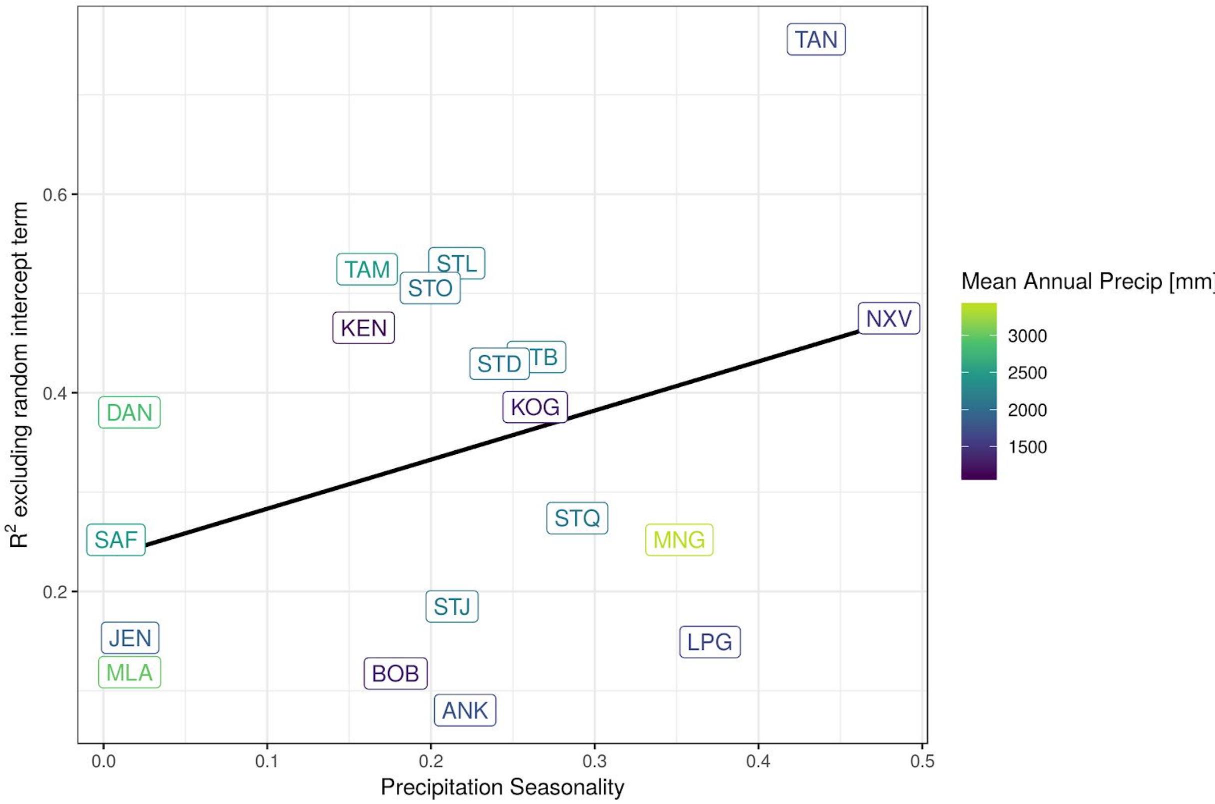
SM Figure 2. Site level downscaled monthly estimate of mean temperature (Tmean) (black) are compared with TerraClimate (blue).



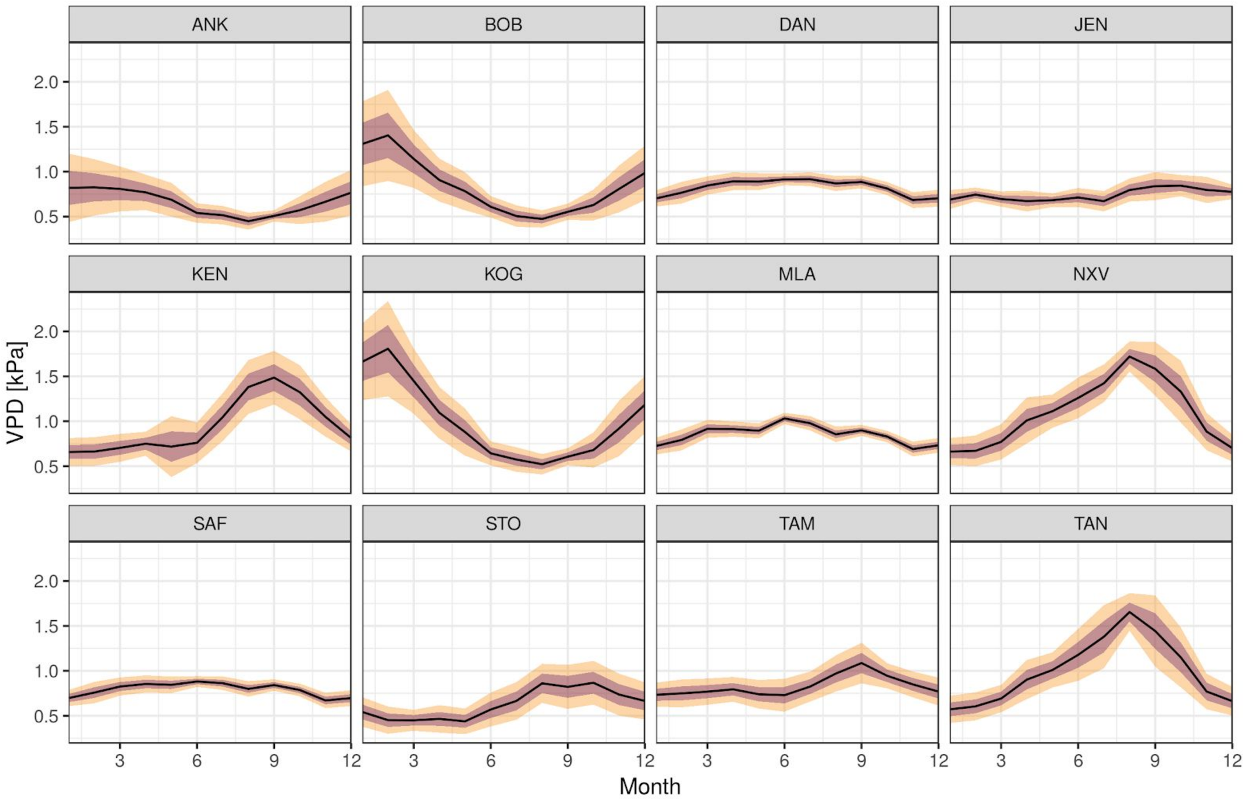
SM Figure 3. Site level downscaled monthly estimate of mean vapor pressure deficit (VPDmean) (black) are compared with TerraClimate (blue).



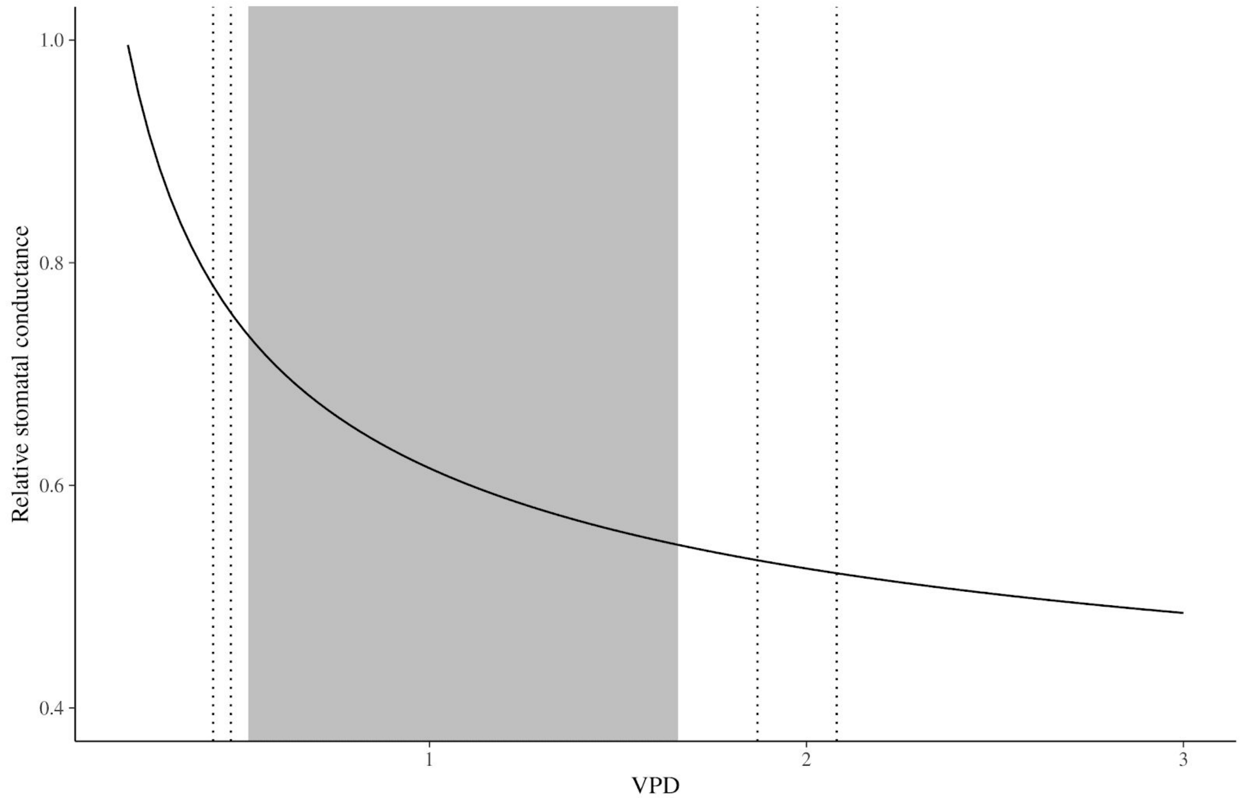
SM Figure 4. The Pearson correlation coefficient is presented for the meteorological variables tested and or retained in the final seasonal and aseasonal wet forest models.



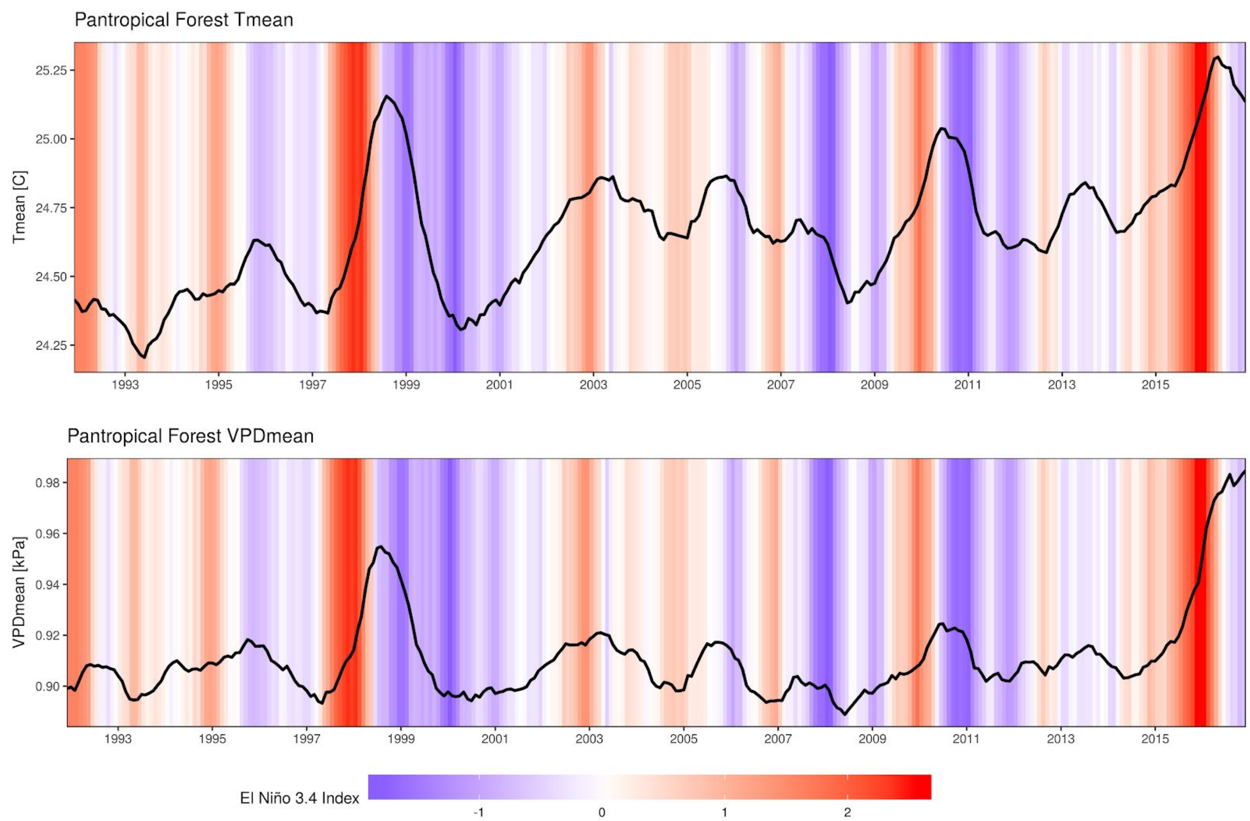
SM Figure 5. The R^2 (excluding random effects) explained by the two statistical models plotted against precipitation seasonality, where a higher value indicates that rainfall is concentrated into a shorter season.



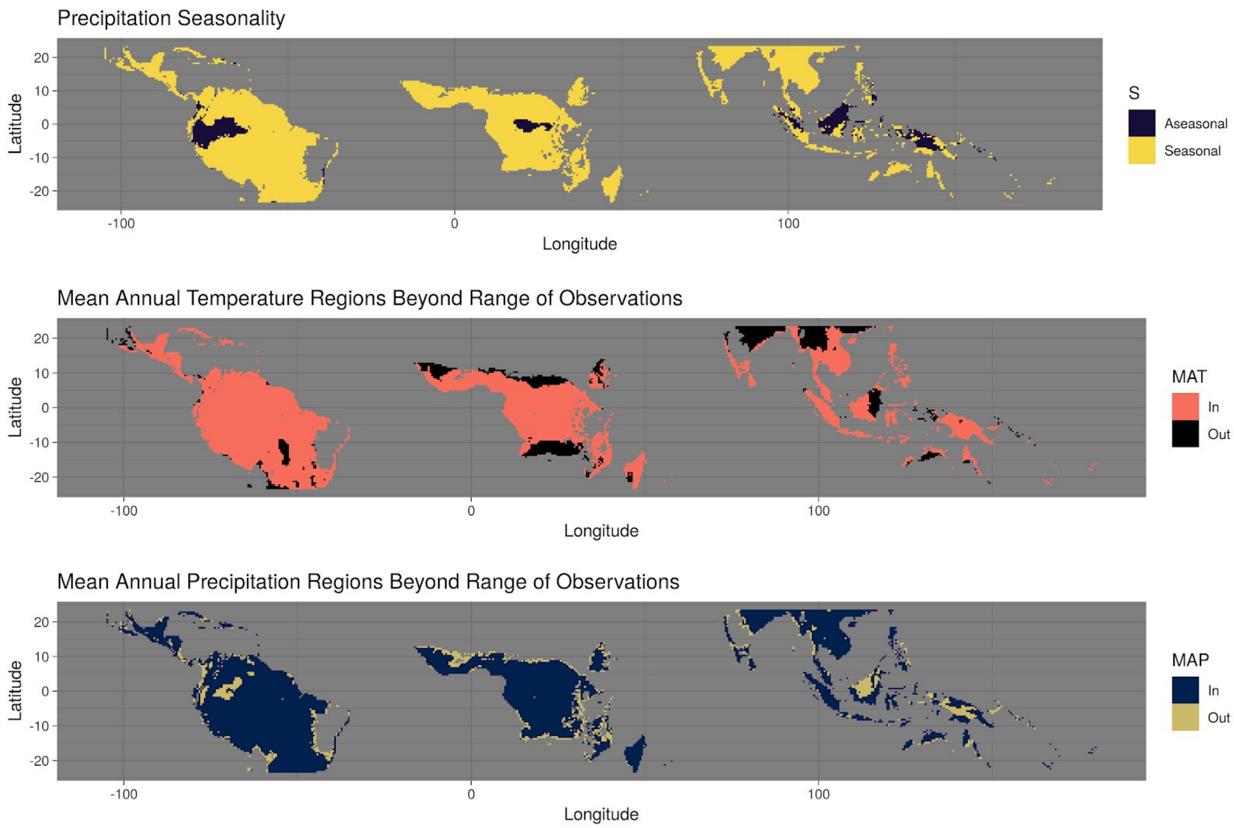
SM Figure 6. The long-term monthly mean of VPD (VPDmean$_{\mu}$) (black line) with the shaded regions representing the range of VPDmean at 1 and 2 standard deviations from VPDmean$_{\mu}$.



SM Figure 7. Relative stomatal conductance using the Medlyn approximation (Medlyn et al., 2011) is plotted against the mean monthly range of vapor pressure deficit [kPa]. The dotted lines represent one and two units of standard deviations beyond (anomalies from the monthly mean conditions in the context of this study) the mean monthly ranges.



SM Figure 8. The Pantropical forest region moving 12-month mean of the air temperature (Tmean) and vapour pressure deficit (VPDmean). Data source is TerraClimate.



SM Figure 9. Areas where precipitation seasonality is greater and or less than 0.05 are shown. The Aseasonal areas with S < 0.05 highlighted here show where the aseasonal wet forest model was applied. The seasonal forest model was applied to all other regions.