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Key Points:

- Mean vapor pressure deficit (VPD) calculated from monthly data is lower than that derived from daily data
- Using mean temperature to calculate VPD underestimates the true value more than using maximum and minimum daily temperatures
- Correlations between annual wildfire extent and annual VPD are not highly sensitive to how VPD is calculated in the western United States

Supporting Information:

Supporting Information may be found in the online version of this article.

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Influence of Time-Averaging of Climate Data on Estimates of Atmospheric Vapor Pressure Deficit and Inferred Relationships With Wildfire Area in the Western United States

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Abstract Vapor pressure deficit (VPD) is a driver of evaporative demand and correlates strongly with wildfire extent in the western United States (WUS). Vapor pressure deficit is the difference between saturation vapor pressure (e_s) and actual vapor pressure (e_a). Because e_s increases nonlinearly with temperature, calculations of time-averaged VPD vary depending on the frequency of temperature measurements and how e_a is calculated, potentially limiting our understanding of fire-climate relationships. We calculate eight versions of monthly VPD across the WUS and assess their differences. Monthly VPDs calculated from daily data are 2%–6% higher, and more accurate, than when calculated from monthly data. Using daily maximum and minimum temperature, instead of mean, increases VPD by ∼20%, but can overestimate true values depending on how e_a is calculated. These differences do not meaningfully impact correlations with annual wildfire area, however, suggesting our understanding of historical fire-VPD relations is not very sensitive to how VPD is calculated.

Plain Language Summary Understanding the relationships between climate and wildfire is crucial, especially in the western United States (WUS), where wildfire sizes and impacts have increased rapidly in recent decades. The vapor pressure deficit (VPD), which is a key component of the atmosphere's evaporative demand and thus an important influence on fuel moisture, is commonly treated as an indicator for fire potential. The VPD is calculated from temperature and humidity, but if these variables cannot be measured on a second-by-second basis, then calculations of VPD are imperfect estimates. How much does this imprecision matter to our understanding of fire-climate relations? Here we show that using time-averaged temperature and humidity does indeed cause systematic biases in estimates of monthly mean VPD, and reduces accuracy of month-to-month variability. Despite this, methodological choice had only minimal effects on correlation between annually averaged VPD and annual wildfire area in the WUS. This suggests that monthly data is sufficient for analyses of statistical linkages between VPD and annual (or seasonal) area burned, though it is likely that calculation methods could influence inferred impacts of daily or sub-daily VPD variations on fire and could produce meaningful differences in projections of future VPD.

1. Introduction

Atmospheric vapor pressure deficit (VPD), defined as the difference between saturation vapor pressure (e_s) and actual vapor pressure (e_a), is a critical indicator of atmospheric aridity (Seager et al., 2015). The VPD is a key metric for understanding how the atmosphere dries fuels, and it has been shown to be closely related to forest burned in the western United states (WUS) (Abatzoglou & Williams, 2016; Balch et al., 2022; Williams et al., 2019; Williams, Seager, Macalady, et al., 2014). The e_s increases exponentially as a function of temperature via the Clausius-Clapeyron relation (Figure 1a) and e_a is generally derived from either dew point temperature (T_d) or the combination of relative humidity (RH) and e_s. Although time-averaged temperature is often used to calculate e_s for convenience, this approach underestimates true e_s since positive temperature excursions drive larger e_s responses than do negative ones. Biases in e_s due to time-averaged temperature then propagate to biases in e_a if e_a is estimated from RH and e_s. However, it is unclear how our assessments of historical fire-VPD relationships may be affected by use of monthly mean data, ignoring the diurnal cycle of temperature, or use of time-averaged RH to estimate e_a, when estimating time-averaged VPD.

While previous research has either assessed the relationship between VPD and fire or examined the influence of calculation method on VPD variability and trends, none, to our knowledge, has analyzed how different VPD calculation methods may influence the apparent relationship between VPD and wildfire. For instance, Yuan et al. (2019) demonstrated differences in VPDs calculated from various climate datasets but they did not examine the effects of estimating VPD from monthly versus daily climate data, or the effects of using average temperature (T_{mean}) versus accounting for the diurnal cycle through use of daily maximum and minimum temperatures (T_{max} and T_{min}). In addition, Howell and Dusek (1995) found that different VPD calculation methods can lead to different estimates of evapotranspiration in the United States southern Great Plains, generally consistent with findings of Abtew and Melesse (2013) in southern Florida. However, how choices among methodologies to estimate VPD impact our impression of fire-VPD relationships is still unclear. In particular, VPD is often calculated using monthly climate data for fire studies (Brey et al., 2021; Grünig et al., 2023; Holden et al., 2018; Williams, Seager, Berkelhammer, et al., 2014; Williams, Seager, Macalady, et al., 2014), but the non-linear response of e_s to temperature could cause substantial differences in time series of monthly, seasonal, or annual VPD if daily or sub-daily data were used instead. This is exemplified in Figure 1b, where we use meteorological observations from a weather station in northern Arizona to show how the above-described methodological choices result in a diversity of estimates of monthly VPD, none correlating perfectly with best-estimates derived from hourly data. Therefore, a comprehensive comparison of the effects of using different variables and temporal resolutions for VPD calculations is needed to better understand the importance of these methodological choices for analyses of fire-climate relations.

Here, we evaluate how different methods, including use of daily T_{max} and T_{min} versus T_{mean}, use of T_d versus RH, and use of daily versus monthly mean data, affect time series of regionally averaged annual and seasonal VPD, and whether the degree to which these choices affect our understanding of the fire-climate relationship in the WUS.

2. Materials and Methods

2.1. Climate Variables

We acquired daily T_{max} and T_{min}, T_d and RH from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) data set (Daly et al., 2021), which is one of the most widely used climate datasets for the conterminous U.S. with a 4 km resolution. We estimated T_{mean} as the mean of T_{max} and T_{min}. For estimates of daily and monthly mean RH we assumed T_d was constant throughout the day and month, respectively. For calculations of daily VPD from T_{max}, T_{min} and RH, we estimated daily mean RH to be the average of daily maximum and minimum RH, which we assumed to co-occur with T_{max} and T_{min}, respectively. We also used in-situ hourly climate data from the U.S. Climate Reference Network stations (Diamond et al., 2013) to evaluate the accuracy of monthly VPD estimates, and the VPD calculated from hourly data is treated as “true” VPD in our study (Figure S1 in Supporting Information S1).

2.2. Fire Data

We utilized the Western US MTBS (Monitoring Trends in Burn Severity)-Interagency version 2 (WUMI2) wildfire database (C. Juang & Williams, 2024) from 1984 to 2020, along with the Moderate Resolution Imaging Spectroradiometer (MODIS) version 6.1 burned area product (Giglio et al., 2021) from 2001 to 2023. Both datasets include maps of monthly area burned that we gridded to 1 km spatial resolution. For each of 19 Bailey's ecoregions in the WUS (Bailey, 2016; Figure S2 in Supporting Information S1), we calculated a record of annual area burned in forested and non-forested areas (Figures S3 and S4 in Supporting Information S1) for 1984 to 2023, where the WUMI2 data were used for 1984–2020 and extended through 2021–2023 using MODIS calibrated to WUMI2. The calibration used the linear relationship between WUMI2 and MODIS annual burned area during the 2001–2020 period of overlap. This relationship was applied to MODIS burned area from 2021 to 2023 to obtain the WUMI-equivalent burned area during 2021–2023. The reconstructed WUMI burned area from 1984 to 2023 was used in our analysis. To distinguish forest from non-forest areas we calculated a 1 km grid of fractional forest coverage from the 250 m map of forest classifications from Ruefenacht et al. (2008).

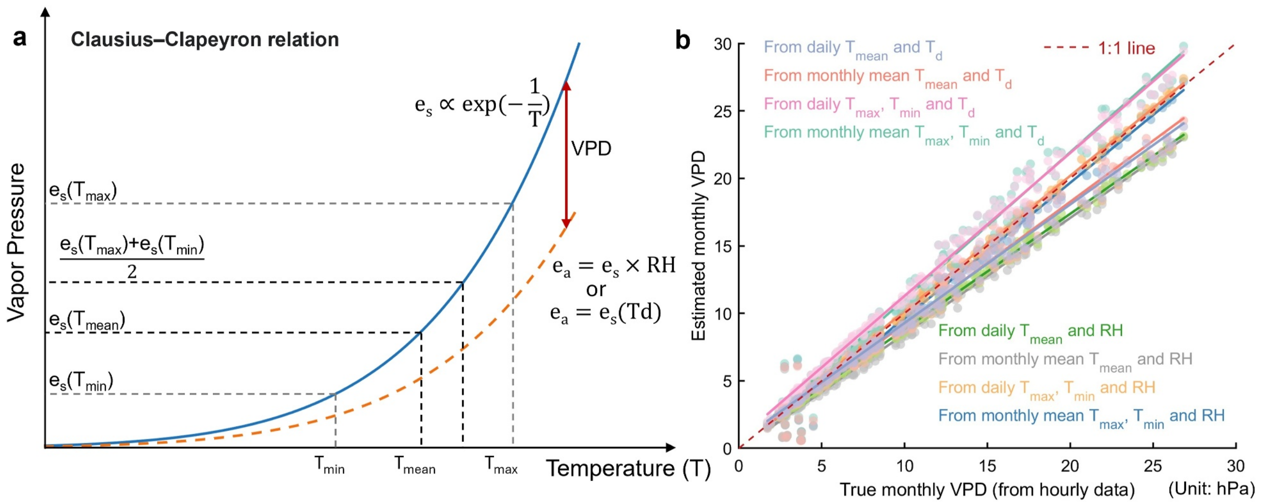

Figure 1. (a) Illustration of the relationship between saturation vapor pressure (e_s) and temperature (T) based on the Clausius-Clapeyron relation (e_a: ambient vapor pressure; RH: relative humidity; T_d: dew point temperature; and T_{min}, T_{mean}, and T_{max}: minimum, mean, and maximum daily temperature), and (b) Scatter plots of eight versions of monthly vapor pressure deficit (VPD) against "true" VPD calculated from hourly station data from 2008 to 2023 in northern Arizona (location in Figure S1 in Supporting Information S1). Solid lines in (b) represent linear regression fits.

2.3. Methods

We used the gridded climate data described in Section 2.1 to produce eight gridded datasets of monthly mean VPD (Figure S5 in Supporting Information S1). Four were produced directly from the daily climate grids and the other four were produced from monthly means of the daily grids. Both sets of four VPD calculations were produced using the same methods, with the exception of one set being calculated from daily data and one being calculated from monthly. The four methods to calculate VPD are shown in Equations 1–4 (the Clausius-Clapeyron formulation to calculate e_s from temperature was the same in all calculations; Equation 5). In the first method (VPD$_1$; Equation 1), e_s is calculated as the average of e_s at T_{max} and e_s at T_{min} (Equations 5–6) and e_a is calculated from T_d (Equation 7). The second method (VPD$_2$; Equation 2) differs from VPD$_1$ only in that e_s is calculated from T_{mean}. The third and fourth methods (VPD$_3$ and VPD$_4$), respectively parallel those for VPD$_1$ and VPD$_2$ except that e_a is calculated from e_s and RH instead of T_d (Equations 8 and 9).

$$\mathrm{VPD}_1 = e_s(T_{\mathrm{maxmin}}) - e_a(T_{\mathrm{d}}) \tag{1}$$

$$\mathrm{VPD}_2 = e_s(T_{\mathrm{mean}}) - e_a(T_{\mathrm{d}}) \tag{2}$$

$$\mathrm{VPD}_3 = e_s(T_{\mathrm{maxmin}}) - e_a(T_{\mathrm{maxmin}}, \mathrm{RH}) \tag{3}$$

$$\mathrm{VPD}_4 = e_s(T_{\mathrm{mean}}) - e_a(T_{\mathrm{mean}}, \mathrm{RH}) \tag{4}$$

In which,

$$e_s(T) = e_s(T_0) \times \exp\left(\frac{\mathrm{L}}{R_{\mathrm{w}}}\left(\frac{1}{T_0} - \frac{1}{\mathrm{T}}\right)\right)(T \text{ is } T_{\mathrm{mean}} \text{ or } T_{\mathrm{max}} \text{ or } T_{\mathrm{min}}) \tag{5}$$

$$e_s(T_{\mathrm{maxmin}}) = \frac{e_s(T_{\mathrm{max}}) + e_s(T_{\mathrm{min}})}{2} \tag{6}$$

$$e_a(T_d) = e_s(T_0) \times \exp\left(\frac{\mathrm{L}}{R_{\mathrm{w}}}\left(\frac{1}{\mathrm{T}_0} - \frac{1}{\mathrm{T}_{\mathrm{d}}}\right)\right) \tag{7}$$

$$e_a(T_{\mathrm{mean}}, \mathrm{RH}) = e_s(T_{\mathrm{mean}}) \times \frac{\mathrm{RH}}{100} \tag{8}$$

$$e_a(T_{\mathrm{maxmin}}, \mathrm{RH}) = e_s(T_{\mathrm{maxmin}}) \times \frac{\mathrm{RH}}{100} \tag{9}$$

Where $e_s(T_0) = 6.11$ hPa is the saturation vapor pressure at a reference temperature T_0 (273.15 K), L (2.5×10^6 J/kg) is the latent heat of evaporation for water, and R_w (461.52 J/(kgK)) is the specific gas constant for water vapor (Shaman & Kohn, 2009). After calculating the eight versions of monthly gridded VPD, we produced annual (calendar-year) means for VPD-wildfire correlation analyses. We also produced an alternative annual VPD set representing just the mean from March–October, as the period beginning in March and ending in late summer or fall has been shown previously to be when correlations between VPD and annual area burned are strongest in this region (Abatzoglou & Williams, 2016; Williams, Seager, Berkelhammer, et al., 2014, 2019).

To explore how VPD methodology may affect our interpretation of VPD-wildfire relationships, we correlated the eight versions of annual VPD time series against annual burned area for forested and non-forested areas from 1984 to 2023. As a supplementary analysis we repeated all correlation analyses focusing only on area burned during May–October, when the vast majority of WUS wildfire area occur, and for these analyses we considered VPD during the shorter March–October window. In addition to correlation analyses focused on the entire WUS, we also examined burned area-VPD relationships for each of the 19 Bailey's ecoprovinces within (Bailey, 2016). Because of the exponential relationship between VPD and burned area (Juang et al., 2022), we performed logarithmic transformation to the burned-area time series prior to correlation analysis.

3. Results and Discussions

3.1. Comparison of VPD Methodologies

Figure 2 compares the time series of eight versions of mean annual WUS VPD, as well as their standardized counterparts. Different VPD calculation methods have large effects on the mean annual values (Figures 2a and 2b) but negligible effects on the relative magnitudes of annual variations in mean VPD, as represented by standardized time series with identical mean and variance (Figures 2i and 2j). VPDs calculated using T_{max} and T_{min} for e_s (VPD_1 and VPD_3) generate significantly ($p < 0.05$) higher values compared to those using $\mathrm{T}_{\mathrm{mean}}$ (VPD_2 and VPD_4) (Figures 2c and 2d). VPD_1 exhibits the largest magnitude, followed by VPD_3, VPD_2 and VPD_4, with VPD_1 being 31.8% and 29.5% higher than VPD_4 (Figures 2a and 2b).

The station analysis indicates no substantial improvement in correlation with "true" monthly means of VPD (calculated from hourly data) when estimating monthly VPD from monthly means of T_{min} and T_{max} instead of T_{mean}, or T_d instead of RH ($\Delta R^2 < 0.03$). On the other hand, all four versions of monthly VPD estimates that are based on monthly mean data exhibit systematic biases in mean VPD: T_{max}, T_{min}, and T_d ($\mathrm{VPD}_{1(\mathrm{month})}$) overestimates true VPD by ~11% whereas $\mathrm{VPD}_{2\text{–}4(\mathrm{month})}$ underestimate true VPD by 7%–17% (Figures S6a–S6d in Supporting Information S1).

The VPDs estimated from daily climate are significantly higher than those from monthly climate (Figures 2a–b and 2e–h), consistent with the station results in Figure 1b and Figure S6 in Supporting Information S1. Our analyses of hourly station data indicate that monthly means of VPD based on daily climate are better correlated with true values, with R^2 higher than 0.98 for all four calculation methods (Figures S6e–S6h in Supporting Information S1). However, use of daily data further enhances the positive bias found when VPD is estimated from T_{max}, T_{min}, and T_d ($\mathrm{VPD}_{1(\mathrm{month})}$ and $\mathrm{VPD}_{1(\mathrm{day})}$) (Figure 1b, Figure S6e in Supporting Information S1). The other three methods of estimating VPD from daily data ($\mathrm{VPD}_{2\text{–}4(\mathrm{day})}$) reduce the magnitudes of the negative biases caused by use of monthly data. Overall, use of daily T_{max}, T_{min} and RH ($\mathrm{VPD}_{3(\mathrm{day})}$) yields the best agreement with true monthly mean VPDs in terms of minimal bias and largest R^2 (Figure S6g in Supporting Information S1). We observe the same general results when we evaluate time series of monthly VPD and March–October mean VPD (Figures S7–S8 in Supporting Information S1).

Although the eight versions of WUS VPD have different means (and variances), the time series of mean annual WUS VPD are all very well correlated with each other ($R^2 > 0.98$). In Figures 2i and 2j, we show that when the 8 VPD time series from Figures 2a and 2b are standardized to have a mean of zero and standard deviation of one, they are nearly identical in terms of interannual variability and trend. In all cases, we calculate that trends in temperature and humidity (mostly warming) caused WUS mean annual VPD to increase by about two standard deviations from 1984 to 2023. This is also true when VPD during just March–October is considered (Figure S8 in

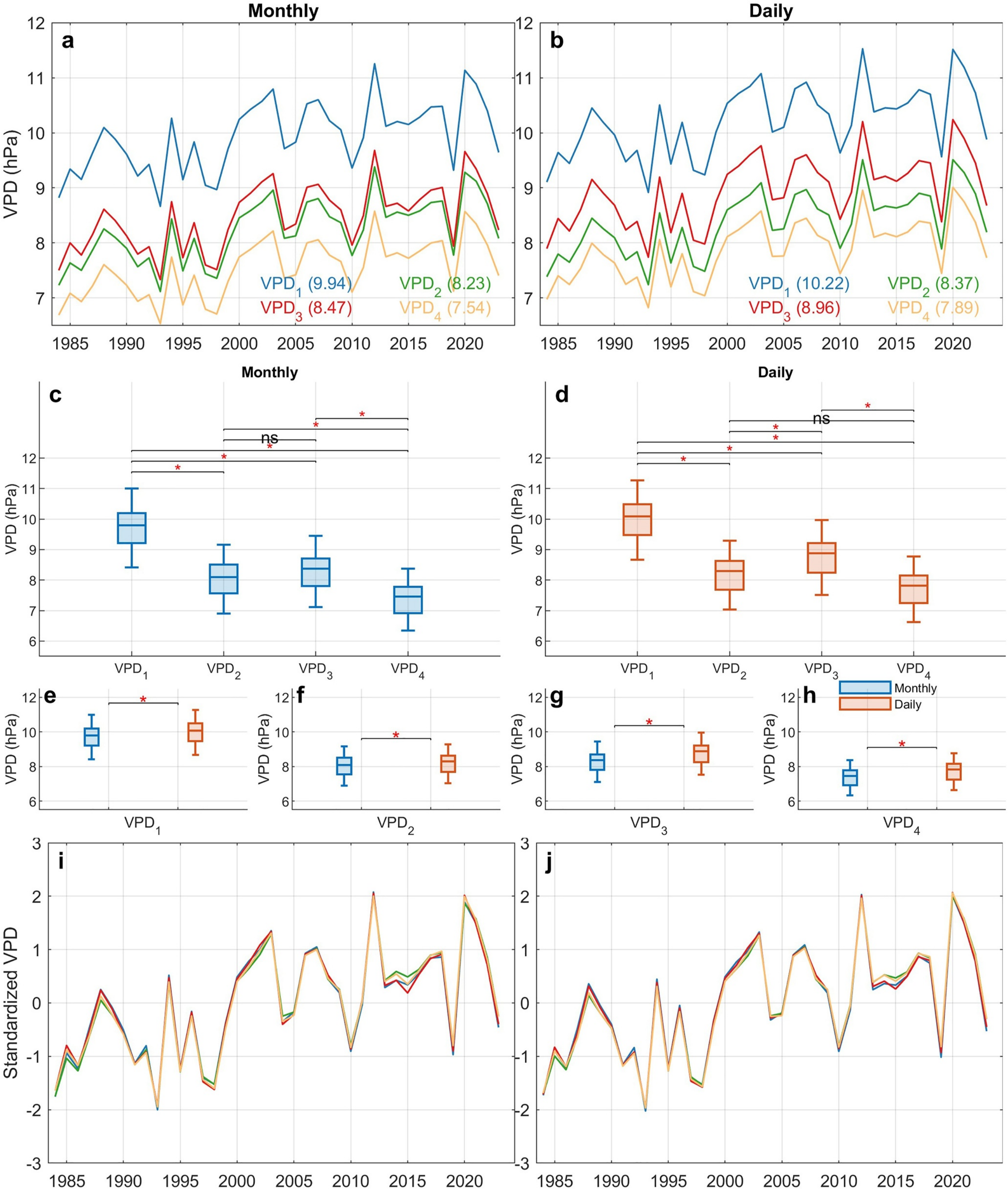
Monthly
Daily
a
b
VPD (hPa)
VPD1 (9.94)
VPD2 (8.23)
VPD3 (8.47)
VPD4 (7.54)
VPD1 (10.22)
VPD2 (8.37)
VPD3 (8.96)
VPD4 (7.89)
c
d
ns
Monthly
Daily
e
f
g
h
i
j
Standardized VPD

Figure 2.

Supporting Information S1). In addition, the spatial patterns of mean VPD across WUS are extremely similar among the eight versions (Figures S9a–S9j in Supporting Information S1) with generally small variation among each other (Figures S9k–S9l in Supporting Information S1), indicating that our finding of high temporal covariability among the 8 VPD versions also extends to spatial covariability.

3.2. Fire-VPD Relationships

As would be expected from the above finding that standardized time series of WUS VPD are highly similar across the 8 VPD methods, we find that correlations between WUS annual VPD and wildfire area are insensitive to VPD methodology (Figure 3). Correlations are very strong ($R^2 = 0.85$–0.87) for forest-fire area (blue dots) and considerably weaker ($R^2 = 0.31$–0.33) in non-forested regions (orange dots), likely due to fuel limitations in many non-forested areas. These results are consistent when we alternatively consider May–October burned area versus March–October VPD, with the exception that correlations in non-forested areas are somewhat reduced ($R^2 = 0.24$–0.26) (Figure S10 in Supporting Information S1).

We further investigate fire-VPD relationships across the 19 WUS ecoprovinces. In each ecoprovince, we show how annual VPD correlates with wildfire area within forested and non-forested areas (Figure 4). Consistent with the all-WUS results, the method used to calculate VPD had minimal effect on correlations between regional annual area burned and VPD (Figure 4). Across ecoprovinces, forested areas consistently exhibited higher correlations than non-forested areas. Area-weighted mean ecoprovincial correlations ranged from 0.56 to 0.57 ($R^2 = 0.31$–0.33) across the 8 VPD methods for forested areas and from 0.20 to 0.21 ($R^2 = 0.04$–0.05) for non-forested areas. Consistent with the interpretation that more positive correlations between VPD and area burned are promoted by fuel availability, the weakest correlations for non-forested regions generally occur in desert areas with relatively sparse vegetation coverage and areas where human population and land use may strongly limit the potential for large wildfires. These ecoprovince correlation results were essentially unchanged when we considered the alternative temporal windows of March–October for VPD and May–October for area burned (Figure S11 in Supporting Information S1).

4. Conclusions

Prior work has established a strong relationship between wildfire activity in the western United States (WUS) and the atmospheric VPD. However, VPD responds non-linearly to temperature and therefore interpretations of fire-VPD relationships could be sensitive to the temporal resolution of the temperature data used as well as whether ambient vapor pressure is derived from dew point (T_d) or RH. Here, we calculated eight versions of VPD to test the effects of (a) using daily versus monthly climate data, (b) accounting for the diurnal cycle through use of daily maximum and minimum temperature (T_{max} and T_{min}, respectively) versus use of mean temperature (T_{mean}), and (c) use of T_d versus RH. First, considering weather stations where hourly data are available to calculate the best estimates of true VPD, we find that among the 8 methods to estimate monthly means of VPD, the method that uses daily measures of T_{max}, T_{min} and RH yields values that are most closely aligned with true VPD. Methods that rely on monthly mean data or neglect the diurnal temperature cycle generally underestimate true VPD, though use of T_{max} and T_{min} in combination with T_d tends to overestimate VPD.

Despite important differences in magnitude and variability, the 8 versions of monthly VPD are extremely well correlated in time and space. That is, including additional temporal information through use of daily versus monthly data, or by accounting for the diurnal cycle in temperature through use of T_{max} and T_{min}, has only a slight influence on relative variations in monthly, seasonally, or annually averaged VPD. Because all methodological choices lead to nearly identical monthly, seasonal, or annual time series of regionally averaged VPD (after differences in means and variances are standardized), correlations between VPD and WUS wildfire area from 1984 to 2023 are insensitive to the VPD method used.

Figure 2. (a–b) Annual time series of the 8 calculations of WUS mean vapor pressure deficit (VPD) from 1984 to 2023. "Monthly" and "Daily" refer to VPDs calculated from monthly and daily means, respectively. The numbers in parentheses in (a–b) represent mean values. Box plots of (c–d) Kruskal-Wallis test (Kruskal & Wallis, 1952), and (e–h) Wilcoxon signed-rank test (Wilcoxon, 1992) for eight versions of annual VPD time series. The elements of the boxes represent individual years in the VPD time series shown in (a–b). An asterisk (*) indicates significant differences ($p < 0.05$). (i–j) Annual time series of standardized VPDs, scaled to mean of 0 and standard deviation of 1.

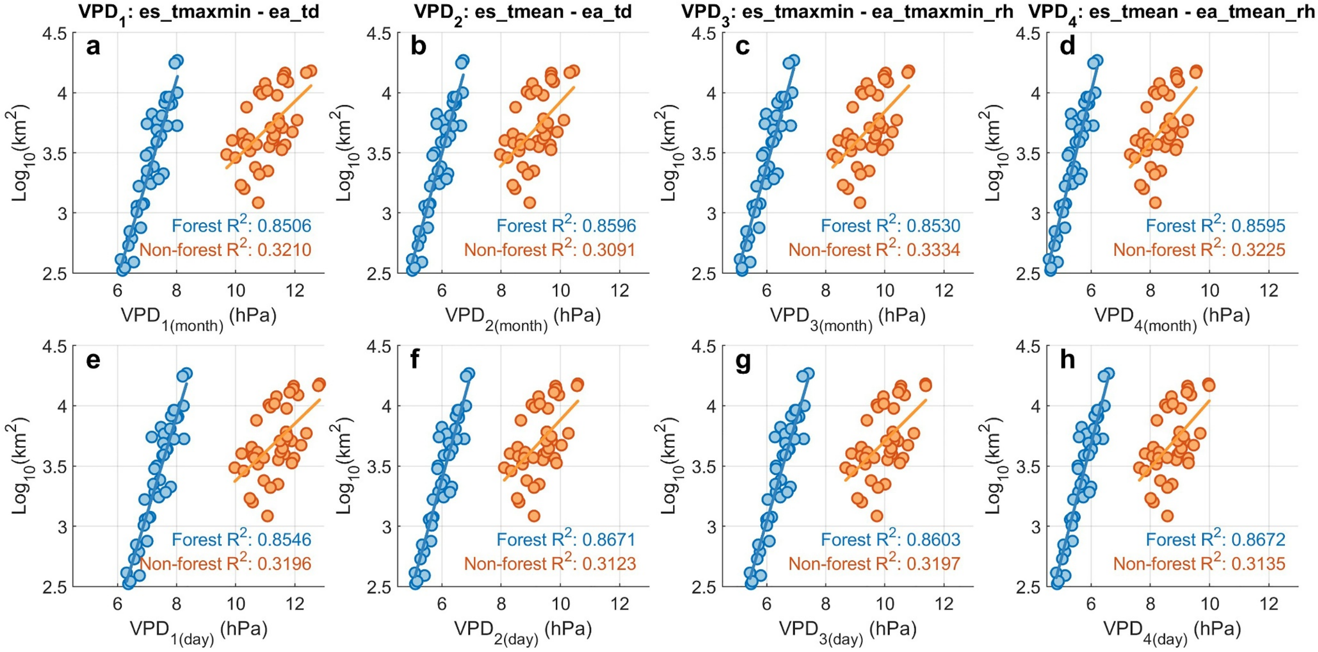

Figure 3. Scatter plots of annual burned areas (log10) versus the eight annual vapor pressure deficit (VPD) versions for forest and non-forest areas in the WUS from 1984 to 2023. Blue and orange: forest and non-forest, respectively. Regression lines: linear fits. VPD is calculated from (a–d) monthly and (e–h) daily data.

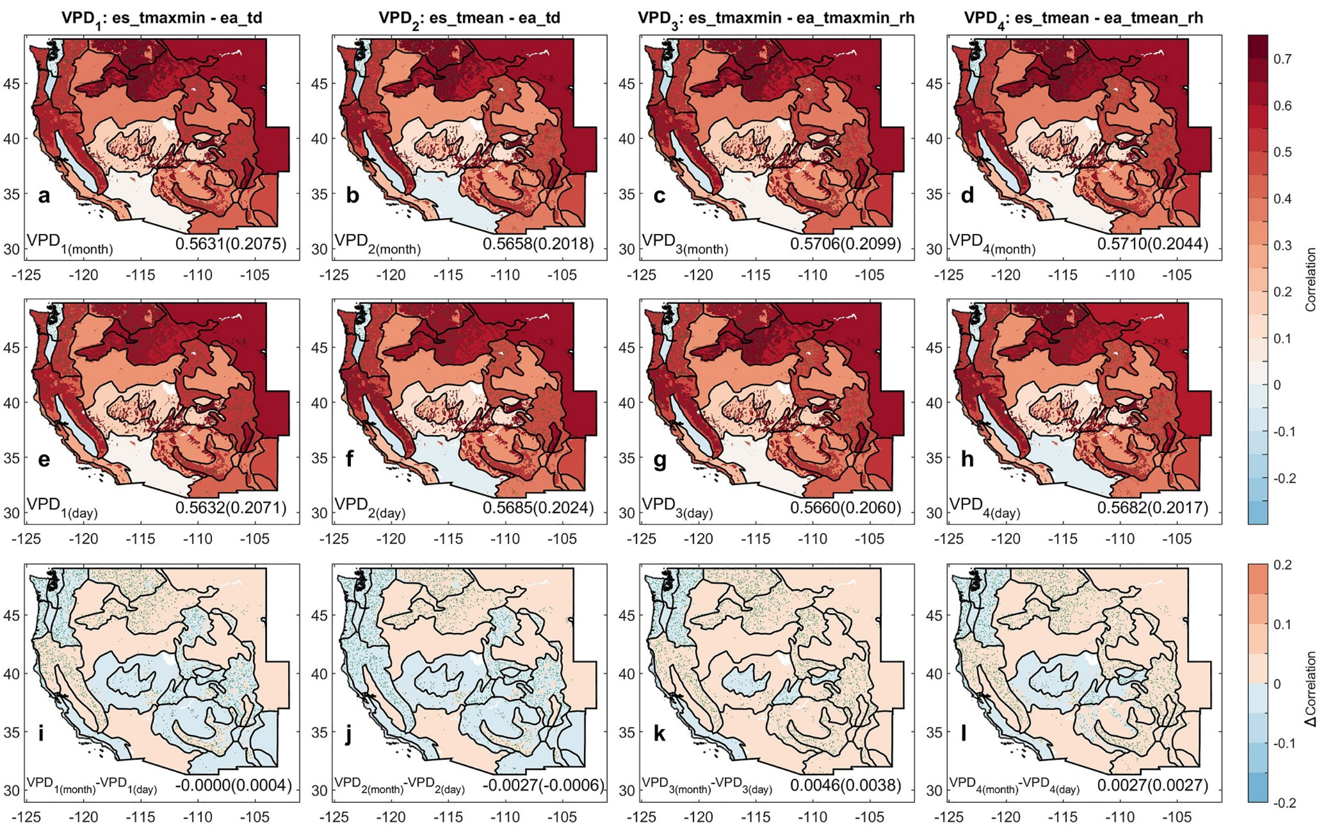

Figure 4. Pearson's correlation between annual burned area and vapor pressure deficit in 19 Bailey's ecoprovinces, calculated and colored separately for forested and non-forested areas within each ecoprovince. Numbers in the lower-right: area-weighted mean correlation across ecoprovinces for forest (non-forest). The weighted area average was obtained using the cosine of latitude. VPDs in (a–d) and (e–h) are calculated from monthly and daily data, respectively. (i–j) Difference between the two overlying rows: $VPD_{(month)}$ minus $VPD_{(day)}$. The forested area (where forest fraction is greater than 0.5) is indicated by dark green stippling.

Importantly, the sensitivity of individual fire events is not limited only to climate conditions averaged over timescales of month and longer (e.g., Balch et al., 2022), so there is surely unique value for daily or sub-daily VPD data in research on fire-climate relations. Further, even though time series of monthly, seasonal, or annual VPD are highly correlated regardless of method, their differences in terms of means and variability are likely important in other fire-related research applications that go beyond the simple correlation analyses explored here. For example, estimates of atmospheric evaporative demand (e.g., the Penman-Monteith equation) used in water-balance calculations (Howell & Dusek, 1995) and hydrological modeling are sensitive to errors in the background mean climate. As such, biases in background mean VPD due to methodological choice are likely to cause biases in calculations of soil moisture balance or fuel moisture. We recommend $VPD_{3(day)}$, which uses daily T_{max}, T_{min}, and RH, because this method led to the strongest agreement with true monthly mean VPD at WUS weather stations (Figure S6 in Supporting Information S1). The combination of T_{max}, T_{min} and T_d in our study also has relatively small bias, and a previous study showed that this combination yields the most accurate VPD estimate in the semi-arid region of the Southern High Plains (Howell & Dusek, 1995). We also demonstrate that monthly meteorological data can be sufficient for VPD estimation when analyzing relationships with the annual burned areas, which can be beneficial for regions lacking high time-resolution data. In addition, although we found fire-VPD correlations to be insensitive to VPD methodology, it is likely that future climate change will drive differential rates of daytime versus nighttime warming, or changes to the distribution of daily mean temperatures or humidities, potentially causing important divergences among estimates of future VPD trends. This could cause VPD-based projections of future wildfire activity to be sensitive to VPD method even if historical VPD-fire relationships were not. Sensitivity of future inferred VPD trends to the calculation method should be the topic of future research.

Data Availability Statement

The WUMI wildfire database can be obtained at DRYAD (C. Juang & Williams, 2024). The MODIS v6.1 burned area is available at NASA's Earthdata Archive (Giglio et al., 2021). Bailey ecoprovince boundaries can be found at the U.S. Department of Agriculture (Bailey, 2016). The fractional forest coverage map is obtained from Ruefenacht et al. (2008). PRISM data can be downloaded from https://prism.oregonstate.edu/. Climate monitoring station data are from the U.S. Climate Reference Network (USCRN) (https://www.ncei.noaa.gov/access/crn/).

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