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Key Points:

- We propose a probabilistic model where we determine changes in the exceedance probability of soil respiration due to changes in variables
- Soil respiration (CO_2 flux) follows a Gaussian-like (bell-shape) pattern with increasing soil temperature
- When temperature exceeds the dew point, soil respiration has the potential to raise up to 60% higher compared to dry condition

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Analyzing High-Frequency Soil Respiration Using a Probabilistic Model in a Semiarid, Mediterranean Climate

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Abstract High-frequency (subhourly) changes in soil respiration (Rs), a critical component of the carbon cycle, are not well documented in semiarid ecosystems. We investigate the response of Rs to subhourly soil temperature (T_{soil}) and soil volumetric water content (VWC) variation in a semiarid ecosystem across a year of highly variable weather. We propose a probabilistic model to estimate the likelihood of Rs exceeding its annual mean ($1.2 \mu\text{mol CO}_2/\text{m}^2\text{s}$), conditioned on different T_{soil} and VWC values. The results show that Rs follows a Gaussian-like pattern as T_{soil} increases, where it follows an upward trend until $\sim 18^\circ\text{C}$, and then begins to decline. Rs remains constant at T_{soil} beyond $\sim 27^\circ\text{C}$. Using our novel conditional probability model, we show both the increasing and decreasing response of Rs to rising T_{soil} through two ranges ($14\text{--}17$ and $20\text{--}23^\circ\text{C}$) where Rs observations show opposing responses. We demonstrate that an increase in T_{soil} from 14 to 17°C causes a rise in Rs by a factor of 1.4 relative to the mean. The proposed model also describes how Rs reduces as T_{soil} continues to increase above $\sim 18^\circ\text{C}$. Considering VWC and T_{soil} into the proposed model, we show that when T_{soil} is low (e.g., 17°C), a rise in VWC yields a decrease of Rs by a factor of 3.6 . However, when T_{soil} is high (e.g., 23°C), Rs increases with increasing VWC by a factor of 2.5 . Overall, the probabilistic model enables us to detect and characterize changes in Rs distribution in response to different environmental variables and thresholds.

1. Introduction

Carbon cycling in semiarid areas may be particularly sensitive to global climate change (Huang et al., 2016) given the ecological and evolutionary dynamics of plants and microbes associated with episodic rainfall input (Huxman et al., 2004) and the magnitude of change in key drivers for these regions of the globe (Weltzin et al., 2003). Carbon dioxide (CO_2) flux from the soil to the atmosphere, also referred to as soil respiration, is a critical component of the carbon cycle (Cable et al., 2011). Soil respiration (Rs) is the second major contributor to the global CO_2 flux and is indeed around 9 times larger than the anthropogenic CO_2 emissions (Carey et al., 2016; Giardina et al., 2014; Raich & Schlesinger, 1992). Rs is associated with the metabolic activity of organisms found in the soil, typically deconstructed as heterotrophs (e.g., decomposing microbes) and autotrophs (e.g., roots and associated symbiotic microbes; Cable et al., 2008). Terrain level, vertical depth of soil, spatial characteristics of the local site, and soil and vegetation type all play roles in the rate of respiration (Cannone et al., 2012; Janssens et al., 2001; Maier et al., 2011). However, the primary abiotic factors controlling the pattern and magnitude of Rs are soil temperature (T_{soil}) and soil volumetric water content (VWC; Liang et al., 2017; Ryan & Law, 2005).

The estimated quantity of carbon stored in and emitted from soil including peatlands, wetlands and permafrost, has been recently studied (Davidson & Janssens, 2006; Scharlemann et al., 2014). However, a significant lack of knowledge exists about the distribution of carbon and Rs of soil in semiarid ecosystem (Schimel, 2010) and the way these variables respond to climate change (Graf Pannatier et al., 2012; Zhong et al., 2016). Thus, any small changes in the underground carbon pools

might have large impacts on carbon flux into the atmosphere (Fabianek et al., 2015; Hirano, 2003; Ryan & Law, 2005).

Several methods have been employed to study the changes of Rs due to climate variability, through field/laboratory experiments (e.g., soil warming; Carey et al., 2016; Hicks Pries et al., 2017; Schindlbacher et al., 2012), models (e.g., Century, Rothamsted Carbon Model [RothC], Earth System Model [ESMs] from Coupled Model Intercomparison Project Phase 5 [CMIP5]) (Lehmann & Kleber, 2015; Todd-Brown et al., 2013; Wieder et al., 2013), and biosphere-atmosphere exchange (e.g., Fluxnet; Phillips et al., 2017), by using deterministic models. These studies provide crucial information about changes of Rs (e.g., standard deviation, mean, and range). However, hardly any endeavor has been made to describe the change in the entire probability distribution of Rs under different hydroclimatic conditions. Such approach provides new insights in detecting changes in the Rs distribution in response to shifts in drivers (i.e., determining changes in the exceedance probability [EP] of Rs due to changes in hydroclimatic variables).

Probabilistic models combined with high-frequency data set have been used in various fields and can reveal valuable information (e.g., analysis of extreme events, snowpack response to warming, nuisance flooding, and compounding effects; e.g., Cheng et al., 2014; Huning & AghaKouchak, 2018; Mazdiyasni et al., 2017; Moftakhi et al., 2017; Papalexiou et al., 2018). The probability density functions (PDFs) used in this study show not only the most likely value (highest density) but also the entire distribution of the expected Rs . Furthermore, we can reflect the distribution of Rs conditioned on any hydroclimate variable of interest (e.g., T_{soil} and/or VWC). The integral of the PDF above a given threshold (i.e., any threshold of interest) represents the EP of Rs (i.e., the likelihood that the designated threshold will be exceeded). By comparing two different exceedance probabilities, we can detect changes in the Rs distribution and therefore measure the impact on Rs given specific hydroclimate conditions. This means, probabilistic models not only provide a thorough insight of Rs dynamics but are also useful tools to characterize the impact of different hydroclimatic conditions on Rs . Using such models in conjunction with our measured subhourly high-frequency data set provides detailed, high-resolution probabilistic analysis on the impacts of hydroclimatic drivers on Rs .

The temperature sensitivity of Rs , described as the rate to which Rs increases or decreases in response to change in temperature, over a wide range of temperatures is not well understood in various biomes (e.g., forest, desert, and semiarid areas; Boone et al., 1998; Cable et al., 2011; Nuanez, 2015). From climate perspective, semiarid terrestrial ecosystems remain data poor, restricting our understanding of how Rs responds to T_{soil} and VWC (Lellei-Kovács et al., 2011; Rey et al., 2011). This may stem from the fact that the Rs rate in semiarid ecosystems is the lowest in comparison with other biomes on Earth (Grünzweig et al., 2009; Oertel et al., 2016), and so their contribution to the total cycle is perceived to be relatively limited. This is not necessarily true as arid/semitropic regions encompass one third of the global dryland (Williams, 1999), and so their contribution to the carbon cycle is significant (Schimel, 2010).

Regarding vegetation, Rs remains challenging on bare soil, due to its complicated biological and physical structure (Eugster & Merbold, 2015). In this perspective, we report subhourly measurements of Rs from bare soil in a semiarid Mediterranean ecosystem located in Southern California, which allows us to characterize pulse-driven dynamics at high frequencies (Evans & Wallenstein, 2012; Huxman et al., 2004; Jenerette et al., 2008). The goal of this study is to characterize the temporal variability of Rs under various hydroclimatic conditions. Using the probabilistic approach, we can assess the impacts of different temperatures and VWC ranges on Rs . In other words, we can more effectively detect the changes in the Rs distribution in response to shifts in drivers (e.g., determining changes in EP in response to increased T_{soil} and decreased VWC). The objectives are (1) to quantify how Rs reacts to changes in T_{soil} and VWC, (2) to describe the impacts of changes in T_{soil} and VWC on the distribution of Rs , and finally (3) to investigate unexpected findings such as the role of dew on Rs in a semiarid area.

2. Materials and Methods

2.1. Site Description

The study area is located at the San Joaquin Marsh Reserve, adjacent to the University of California, Irvine. The San Joaquin Marsh Reserve is within the University of California Natural Reserve System, encompassing more than 817,500 m². It is subdivided into different sections, including man-made and untouched areas.

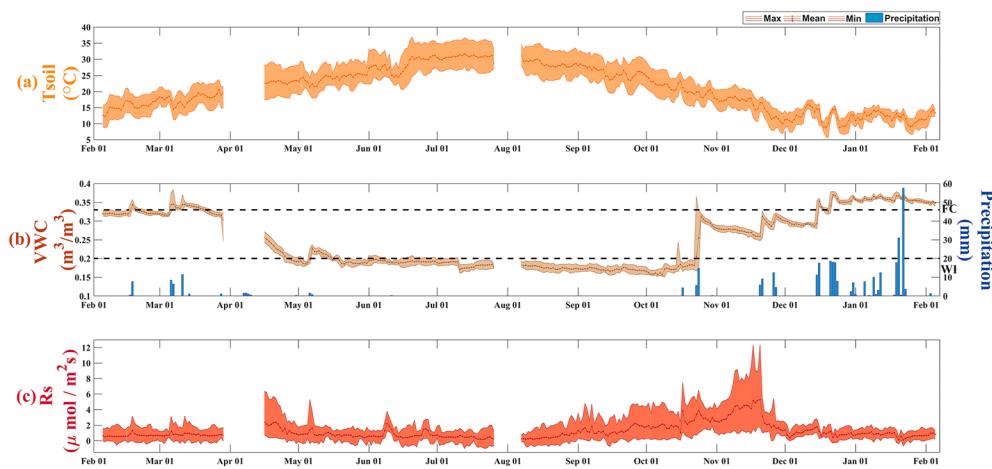


Figure 1. Daily meteorological parameters and R_s from February 2016 to February 2017. Max and min are displayed in solid lines and mean values are shown in dotted solid lines. R_s increases when precipitation happens. But higher precipitation does not always lead to higher R_s above a certain level of precipitation and T_{soil} ; R_s starts to decrease. This effect is shown in November and December. VWC = volumetric water content.

The measurement gauge is located in the untouched area ($33^{\circ} 39' 32.7''\text{N}$, $117^{\circ} 50' 55.9''\text{W}$) at an elevation of 2 m above sea level. This region experiences a Mediterranean climate (i.e., mild, moderately wet winters and warm to hot, dry summers) with an average annual temperature of $\sim 17^{\circ}\text{C}$ and a mean annual precipitation of 300 mm (Bowler, 2007). Investigated soils have been characterized as well drained omni clay with a pH of 8.5, calcium carbonate content of 3% (Bowler, 2007; California Resources Agency, 2007), and soil organic matter content of 3.5%. On average soil organic matter contains 58% carbon (van Bemmelen, 1891), we therefore presume a soil carbon content of 2%. The chemical property of the soil also shows calcium carbonate (CaCO_3) with an amount of 3% (Bowler, 2007; California Resources Agency, 2007; Web Soil Survey [WWW Document], n.d.). In addition, the soil based on the U.S. Department of Agriculture Natural Resources Conservation Service is classified as Omni with a taxonomic classification of fine, montmorillonitic (calcareous), and thermic Fluvaquentic Haplaquolls, Mollisols (Bowler, 2007; California Resources Agency, 2007; U.S. Department of Agriculture Natural Resources Conservation Service, n.d.). The moisture characteristics of the soil in terms of field capacity and wilting point for omni clay have been reported to be 0.33 and $0.20 \text{ m}^3/\text{m}^3$, respectively (Walker, 1989), which are shown as dashed lines in Figure 1b.

2.2. Soil Respiration and Additional Measurements

Soil respiration (R_s) was measured subhourly from February 2016 to February 2017 using an automated R_s system (LI-8100A, LI-COR, Inc., Lincoln, Nebraska, USA). The LI-8100A is an Automated Soil Gas Flux System, which measures CO_2 flux from the soil using a single long-term transparent chamber and an analyzer control unit (ACU). The infrared gas analyzer installed in the ACU measures the change in CO_2 in the chamber. One polyvinyl chloride collar with a diameter of 20.3 cm and height of 11 cm was inserted into the soil to a depth of 6 cm 1 week before measuring R_s to limit soil disturbance and to allow repeated measurements. The vegetation within the collar was cleared off to make sure that the soil remains bare over the entire observation period. The system was programmed to enable five measurements per hour with an observation period of 2 min. During each flux measurement, the chamber vented automatically for 65 s (45 s pre-purge and 20 s postpurge). An umbrella was installed above the ACU to protect the analyzer from sunlight and to avoid overheating.

Simultaneously, soil temperature (T_{soil}) and soil VWC near the chamber at 5-cm depth below ground surface were observed using an auxiliary soil temperature thermistor (LI-COR, Inc., Lincoln, NE, USA) and an ECH_2O model EC-5 (Decagon Devices, Inc., Pullman, WA, USA), respectively. Both sensors were attached to the LI-8100A ACU. The EC-5 determines the VWC by measuring the dielectric constant media using capacitance domain technology (Kočárek & Kodešová, 2012). The system was

powered at the beginning of the observations with a 55-Ah/12 volt battery and a 60-W solar panel but upgraded to a 180 Ah/12 Volt battery with 260-W solar panels after several power failures. Due to the latest upgrade of the battery and solar panels, we limited the observations to five measurements per hour to ensure continuous day and night measurements. Approximately 7% of the Rs data were not captured due to instrument failure and insufficient power supply due to cloudy days.

To confirm the existence and effect of dew on Rs , we performed a short experiment of 2 days in mid-November. In this experiment we measured the soil surface temperature at the study site during night. Night surface soil temperature (T_{soil} surface) inside the collar was obtained using an EasyLog EL-USB-2-LCD temperature data logger (Lascar Electronics Inc., Erie, PA, USA).

Daily meteorological data (e.g., dew point and precipitation) were obtained from the weather station at the John Wayne Airport (SNA), Santa Ana, CA (located within three kilometers from the study area), from the National Oceanic and Atmosphere Administration website (<https://gis.ncdc.noaa.gov/maps/ncei/cdo/hourly>).

2.3. Data Analysis

We use Spearman correlation coefficient (R^2) to evaluate the relationship between Rs and T_{soil} and VWC due to existing time lags. These lags result in an elliptical hysteresis loop (Phillips et al., 2017; Song et al., 2015) and are caused, for instance, through the transport of Rs from various depth layers to the surface (Phillips et al., 2017), resulting in a delay in the Rs observation (Zhang et al., 2015). However, no guideline exists on how Rs data should be analyzed in order to determine the relationship between Rs and T_{soil} (Phillips et al., 2011). We, therefore, use stepwise regression analysis through which we temporally adjust the time series of hydroclimatic parameters by stepwise shifting entire time series in time. Lag time-induced temporal adjustment of hydroclimate parameters and Rs continues till the vectors are synchronized based on the highest value of R^2 . Our results show that, in the studied system, the lag time between Rs and hydroclimate parameters through the entire time series is ~ 6 hr. The stepwise regression technique used here reflects upon strong seasonality in Rs and thus varying lag times (Kuzyakov & Gavrichkova, 2010). The time lag between Rs and hydroclimate parameters for spring (20 March to 20 June), summer (21 June to 21 September), fall (22 September to 20 December), and winter (21 December to 19 March) season is estimated to be ~ 3 , ~ 7 , ~ 4 , and ~ 10 hr, in the studied area, respectively. Henceforward, we use the adjusted time series in this research for further analysis.

To evaluate Rs - T_{soil} and VWC- T_{soil} relationships, we use the mean value of data points existing within a step size of 1 °C. We rank the T_{soil} values from min to max and averaged all associated data points (e.g., Rs and VWC) within the given step size of 1 °C.

We quantify the temperature sensitivity of Rs (ΔRs) and VWC (ΔVWC) using a moving average technique, which removes residuals and reveals the overall trend. By using moving bin average, we calculate the arithmetic mean of several consecutive values of different subsets from the whole data set. The temperature sensitivity (i.e., rate of change) is calculated through consecutive subtraction of the bin-averaged values at two consecutive calculating windows. The mathematical representation of the temperature sensitivity analysis process using moving bin-averaged technique is as follows:

$$\Delta = \frac{1}{x_2} \sum_{t=i+m}^{i+n+m} a_{t_2} - \frac{1}{x_1} \sum_{t=i}^{i+n} a_{t_1} \quad (1)$$

where n , m , i , $a_{t_{1,2}}$, and $x_{1,2}$ represent length of moving average, step size, starting point, measured values (e.g., Rs and VWC) for T_{soil} taking values of t , and number of data points, respectively. It is worth mentioning that the spans include different sample sizes. To calculate the ΔRs , for example, we first rank the T_{soil} values from min to max and then choose the starting point as the smallest observed T_{soil} value (i.e., 5.5 °C). Then we calculate the mean of Rs measured within a span of 5 °C (e.g., T_8 refers to values associated within 5.5 to 10.5 °C) and a step size of 1 °C (e.g., T_9 would encompass the values associated within 6.5 to 11.5 °C). Finally, we subtract the bin-averaged values at the two consecutive bins (T_{9-8}).

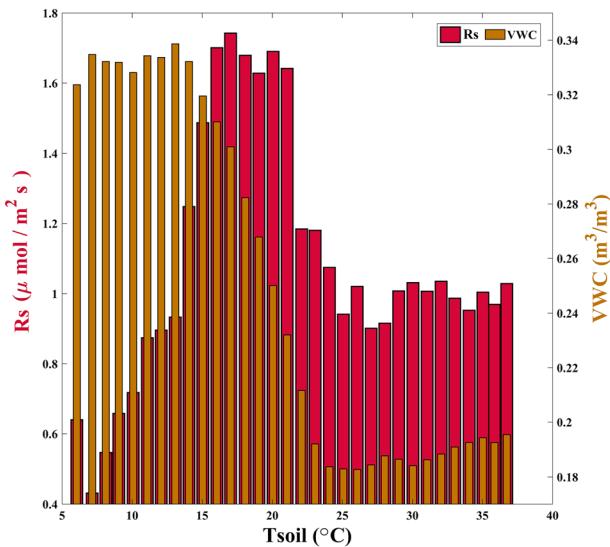


Figure 2. Hourly bin-averaged Rs and volumetric water content (VWC) across T_{soil} ranges. Rs shows a Gaussian pattern and VWC displays a mirrored sigmoid pattern. Rs increases until $\sim 18^{\circ}\text{C}$ with increasing T_{soil} and above Rs decreases with further increase of T_{soil} . Above $\sim 27^{\circ}\text{C}$ Rs stays steady.

Empirical conditional PDFs help to assess changes in the Rs distribution given any hydroclimate variable (e.g., T_{soil} and/or VWC). The PDF of Rs conditioned on one variable (e.g., T_{soil}) and two variables (e.g., T_{soil} and VWC) can be calculated via equations (2) and (3), respectively (Yue & Rasmussen, 2002):

$$f_{Y|X}(y|x) = [f_X(x) \cap f_Y(y)] / f_X(x) \quad (2)$$

$$f_{Y|X}(y|x, z) = [f_X(x) \cap f_Y(y) \cap f_Z(z)] / [f_X(x) \cap f_Z(z)] \quad (3)$$

where $f_X(x)$, $f_Y(y)$, and $f_Z(z)$ represent the marginal probability distribution function of T_{soil} , Rs , and VWC, respectively. The mathematical representation of the EP describes the likelihood of Rs exceeding a given threshold ($Y > y$) for different values of T_{soil} ($X = x_1, x_2, \dots$) and different values of VWC ($Z = z_1, z_2, \dots$). To ensure the results are reliable and limited sample size is not affecting the outcomes, we require at least 100 observation points within a T_{soil} range of $\pm 0.5^{\circ}\text{C}$ to implement analysis. For purposes of visualizations, we limit the Rs range in Figures 5–7 to a max of $5 \mu\text{mol CO}_2/\text{m}^2\text{s}$. Furthermore, we choose the annual mean of Rs ($1.2 \mu\text{mol CO}_2/\text{m}^2\text{s}$) as the threshold of interest with regards to which we calculate the EP. The EP represents the likelihood that Rs exceeds its annual mean, given different hydroclimate conditions. The probability (\widetilde{P}) of Rs (Y) exceeding a certain threshold (here the annual mean of Rs : \bar{y}) is given by the following integrals:

$$\widetilde{P}_x = \int_{\bar{y}}^{\infty} f_{y|x} dy \quad (4)$$

$$\widetilde{P}_{x,z} = \int_{\bar{y}}^{\infty} f_{y|x,z} dy \quad (5)$$

where \widetilde{P}_x and $\widetilde{P}_{x,z}$ represent the shaded area under the PDF curves given by equation (2) in Figures 5 and 7 and equation (3) in Figure 6. The high-frequency data provided through field observations described in section 2.2 enable us to explore if dew presence can describe part of the Rs variance observed in the record. We compared night T_{soil} surface observations from the data logger with minimum values of the air chamber temperature (T_{cham}), which correspond to night temperatures. This seems a reasonable comparison as the chamber is stationed just at a height of ~ 15 cm above the soil surface. The percent difference (PD) quantifies the difference between these two temperature values.

$$PD = \left(\frac{1}{x} \sum (T_{\text{cham,air night}} - T_{\text{soil,surface night}}) / T_{\text{soil,surface night}} \right) * 100 \quad (6)$$

where $T_{\text{cham,air night}}$, $T_{\text{soil,surface night}}$, and x display the minimum value of the night air chamber temperature, night surface soil temperature, and the number of data values, respectively.

3. Results and Discussion

3.1. Temporal Variation of Meteorological Variables and Soil Respiration

Figure 1 shows daily meteorological parameters and Rs data. Figure 1a shows low T_{soil} during the wet season (November–April) and high T_{soil} in the dry season (May–October) and as expected, the temporal variation of VWC follows the precipitation seasonal pattern, that is, Anders and Rockel (2009). It also displays that when VWC is between 0.20 and $0.33 \text{ m}^3/\text{m}^3$, Rs increases with rainfall, while beyond $0.33 \text{ m}^3/\text{m}^3$ when soil becomes saturated (above $0.33 \text{ m}^3/\text{m}^3$ dashed line), Rs remains insensitive to further rainfall inputs. The study area usually receives most of its precipitation during the wet season followed by a dry season with

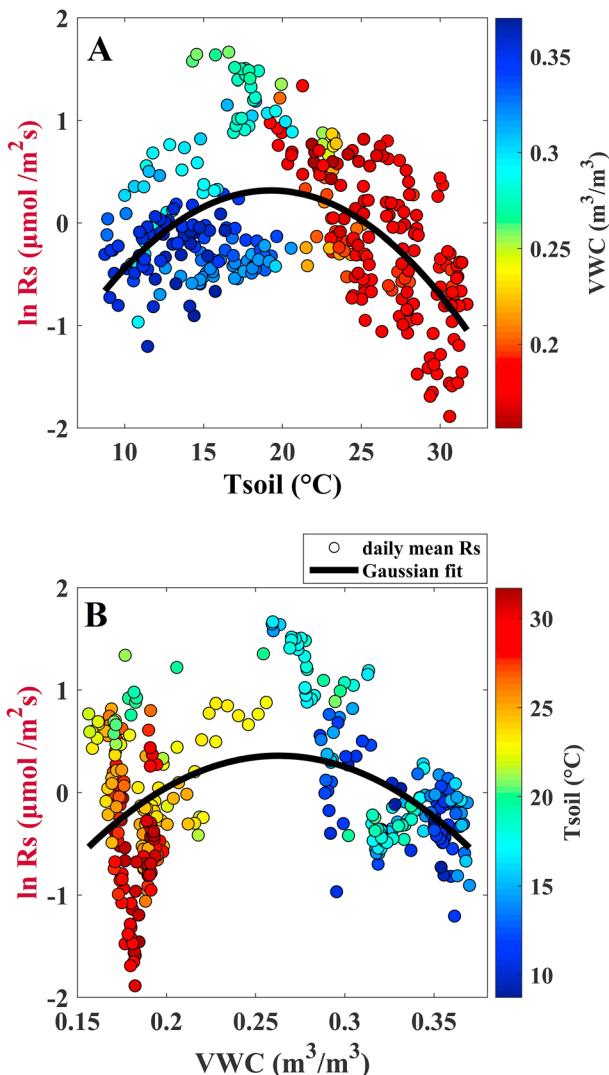


Figure 3. Scatterplot of daily mean values of R_s - T_{soil} (a) and R_s -VWC (b) relationships where the shading of the circles represents the VWC and T_{soil} , respectively. R_s data are transformed by using natural log function to minimize outliers. Correlation for the R_s - T_{soil} and R_s -VWC relationships is $R^2 = 0.28$ and $R^2 = 0.14$, respectively. Gaussian response is fitted to the R_s - T_{soil} and R_s -VWC relationships with the equation: $\ln(R_s) = -0.008821 * T_{soil}^2 + 0.34 * T_{soil} - 2.96$ and $\ln(R_s) = -78.61 * VWC^2 + 41.33 * VWC - 5.07$, respectively.

continuous increase with rising temperature; therefore, the growth must cease and begin to decrease as T_{soil} increases above key levels influencing organismal function (Tuomi et al., 2008). Thus, fitting models like the exponential (Q_{10} model), Arrhenius or Lloyd-Taylor equations that do not take into account the declining trend of R_s after a metabolic threshold have limited applicability for response dynamics prediction of soil to temperature change (BéHráDek, 1930; Carey et al., 2016). These fitting models generally describe an exponential increase of R_s with increasing temperature and can only be used in a narrow temperature range. Previous studies have discussed the inability of these fitting models to represent the response of R_s across a wide temperature range, where a decrease of R_s takes place.

To describe the relationship between R_s - T_{soil} and R_s -VWC in Figures 3a and 3b, we use a log-quadratic T_{soil} (VWC) response function, which is a Gaussian-type model (Carey et al., 2016; Heskel et al., 2016; Lellei-Kovács et al., 2011).

relatively low precipitation. The area received, within the study period, ~348 mm of precipitation in total. Figure 1c shows that over the study period, R_s varies between -1.01 and $12.37 \mu\text{mol CO}_2/\text{m}^2\text{s}$. These respiration rates are eminently high. However, we found only a few very high measurement points ($>10 \mu\text{mol CO}_2/\text{m}^2\text{s}$) and several high values between 6 to $10 \mu\text{mol CO}_2/\text{m}^2\text{s}$; usually R_s rates in semiarid areas are measured between ~ 0.30 and $\sim 2.6 \mu\text{mol CO}_2/\text{m}^2\text{s}$ (Oertel et al., 2016; Wang et al., 2014). The results generally imply that R_s rises following precipitation events, which is compatible with the results from Deng et al. (2012) and Yan et al. (2014).

3.2. Regression Analysis

Figure 2 depicts the variation in R_s and VWC values that are bin averaged within the given step size of 1°C with respect to T_{soil} . VWC plays a significant role in R_s and is, therefore, indispensable to be neglected (Qi et al., 2002). Especially in Mediterranean and semiarid ecosystems it needs to be taken into account, where R_s is highly sensitive to VWC (Chang et al., 2014; Yan et al., 2014). We demonstrate that R_s is limited both when VWC is high and T_{soil} is low and vice versa, which is compatible with Reinsch et al. (2017). By examining how T_{soil} and VWC affect R_s , we indicate that T_{soil} values below 14°C and beyond 27°C and VWC magnitude below $0.20 \text{ m}^3/\text{m}^3$ and beyond $0.32 \text{ m}^3/\text{m}^3$ yield limited R_s . The limitation of R_s at high T_{soil} in other ecosystems has been reported by Portner et al. (2010) and Richardson et al. (2012). VWC shows a mirrored sigmoid response function, which is basically a mirrored S form, across the T_{soil} range (Schulze, 2000). VWC stays around $\sim 0.33 \text{ m}^3/\text{m}^3$ when T_{soil} is below $\sim 14^\circ\text{C}$, and it decreases gradually below wilting point with increasing T_{soil} . At T_{soil} above $\sim 23^\circ\text{C}$, VWC remains nearly constant by $\sim 0.19 \text{ m}^3/\text{m}^3$. High and low VWC diminish the temperature response of R_s due to the potential oxygen limitations and metabolic drought stress, respectively (Chang et al., 2014). Other factors such as CO_2 diffusion into pore spaces and CO_2 dissolution in pH water could also limit the temperature response of R_s (van Haren et al., 2017).

A similarly Gaussian (bell-shape) pattern in the R_s response across the T_{soil} ranges is visible, which corroborates with the findings of Carey et al. (2016) and Portner et al. (2010). Figure 2 shows that below $\sim 18^\circ\text{C}$, R_s increases to nearly $\sim 1.8 \mu\text{mol CO}_2/\text{m}^2\text{s}$ and by exceeding $\sim 18^\circ\text{C}$, R_s decreases to $\sim 1 \mu\text{mol CO}_2/\text{m}^2\text{s}$. Beyond $\sim 27^\circ\text{C}$, R_s remains nearly unchanged with increasing T_{soil} . The latter can be attributed to the fact that biological systems are expected to lower in activity beyond some temperature optima (Schipper et al., 2014). It is not realistic to expect a continuous increase with rising temperature; therefore, the growth must cease and begin to decrease as T_{soil} increases above key levels influencing organismal function (Tuomi et al., 2008). Thus, fitting models like the exponential (Q_{10} model), Arrhenius or Lloyd-Taylor equations that do not take into account the declining trend of R_s after a metabolic threshold have limited applicability for response dynamics prediction of soil to temperature change (BéHráDek, 1930; Carey et al., 2016). These fitting models generally describe an exponential increase of R_s with increasing temperature and can only be used in a narrow temperature range. Previous studies have discussed the inability of these fitting models to represent the response of R_s across a wide temperature range, where a decrease of R_s takes place.

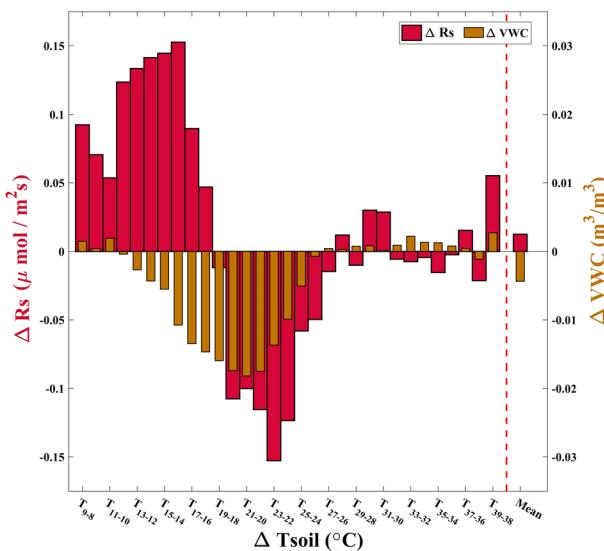


Figure 4. Temperature sensitivity of Rs and volumetric water content (VWC). Temperature sensitivity of Rs is positive $<18^{\circ}\text{C}$ (T_{18-17}), negative in between 18 and 27°C (T_{27-26}) and weak $>27^{\circ}\text{C}$. The mean (right side beyond the red dotted line) represents the average of ΔRs and ΔVWC over the entire temperature range. On average ΔRs and ΔVWC display an increase of $\sim 0.013 \pm 0.086$ ($\mu\text{mol CO}_2/\text{m}^2\text{s}$) and a decrease of $\sim -0.004 \pm 0.007$ (m^3/m^3) per 1°C , respectively.

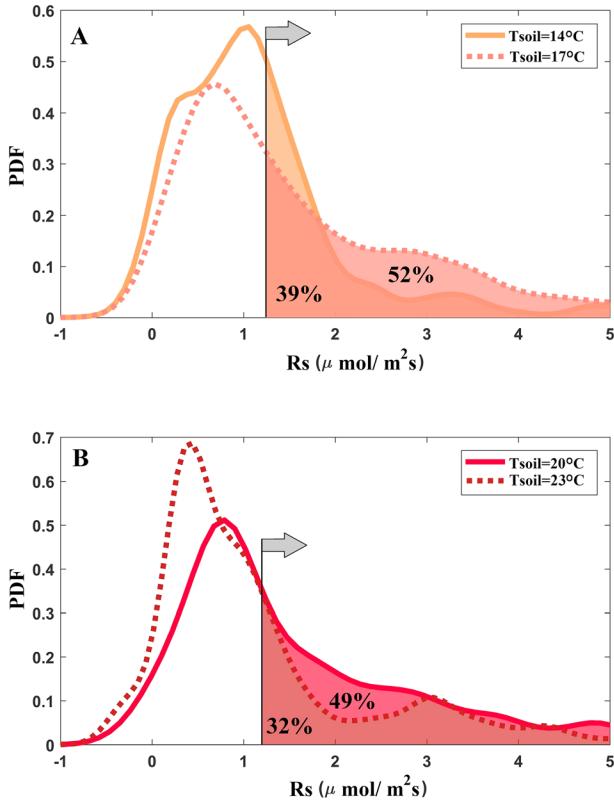


Figure 5. Two panels with conditional probability density functions (PDFs) of Rs under four different T_{soil} scenarios. The panels show the probability of exceeding annual mean of Rs ($1.2 \mu\text{mol CO}_2/\text{m}^2\text{s}$) given different T_{soil} .

$$\ln(Rs) = aX^2 + bX + c \quad (7)$$

where Rs is soil respiration, X is either soil temperature (T_{soil}) or soil VWC, and a , b , and c are variables to be calibrated. We fit this log-quadratic T_{soil} (VWC) response function with daily mean values of Rs . In addition, we display in the z axis the shading of the circles in the panels (a) and (b) as VWC and T_{soil} , respectively. The results are compatible with our findings from Figure 2 where Rs is limited at both low T_{soil} and high VWC and vice versa.

3.3. Temperature Sensitivity of Rs and VWC

Figure 4 shows the temperature sensitivity of Rs (ΔRs) and VWC (ΔVWC) per 1°C change in T_{soil} through moving bin averages (equation (1)). Figure 4 reveals that ΔRs is nonlinear across all T_{soil} ranges, because it responds to a combination of variability in T_{soil} and VWC (Qi et al., 2002). It is also visible that ΔRs is positive at temperatures below $\sim 18^{\circ}\text{C}$ (T_{18-17}) and negative at temperatures between ~ 18 and $\sim 27^{\circ}\text{C}$ (T_{27-26}). Above $\sim 27^{\circ}\text{C}$ a weak (no significant trend) ΔRs is detectable. We conclude that the positive or negative ΔRs indicates an increase or decrease of Rs , respectively. We infer that ΔRs is greatest at low T_{soil} and declines as T_{soil} increases, which is consistent with the finding of Schipper et al. (2014). Tucker and Reed (2016) also concluded a positive ΔRs at low to moderate T_{soil} and a negative ΔRs during summer which is associated with high T_{soil} . A number of studies have described the negative ΔRs above a certain T_{soil} threshold (Cable et al., 2011; Tucker & Reed, 2016). The reason for the weak ΔRs could be due to the low VWC at high T_{soil} or microbial protein denaturation (Carey et al., 2016; Portner et al., 2010). In the ranges of positive, negative, and weak trends, ΔRs is estimated to be $\sim -0.108 \pm 0.050$, $\sim -0.075 \pm 0.054$, and $\sim -0.006 \pm 0.024 \mu\text{mol CO}_2/\text{m}^2\text{s}$, respectively, although ΔRs over the total range of observed temperature exhibits an increasing trend of $\sim 0.013 \pm 0.086 \mu\text{mol CO}_2/\text{m}^2\text{s}$ per 1°C .

In Figure 4, ΔVWC shows a nonlinear relationship with T_{soil} as well. ΔVWC shows a decreasing response below $\sim 27^{\circ}\text{C}$ (T_{27-26}), and above $\sim 27^{\circ}\text{C}$ there is no significant trend visible. During negative and no trend ΔVWC , on average $\sim -0.008 \pm 0.007$ and $\sim -0.001 \pm 0.001 \text{ m}^3/\text{m}^3$ is visible, respectively. Overall, ΔVWC decreases by $\sim -0.004 \pm 0.007 \text{ m}^3/\text{m}^3$ per 1°C .

3.4. Conditional Probability Analysis

Figure 5 displays the conditional PDF of Rs given T_{soil} values from 14 to 23°C with step sizes of 3°C . In order to show both the increasing and decreasing response of Rs to rising T_{soil} (as shown in Figure 2), we have selected two ranges where Rs observations show opposing responses. The shaded area in both panels show the probability of exceeding the annual mean of Rs (\widetilde{P}_x ; equation (4)) given different T_{soil} values. Figure 5a exhibits that when T_{soil} reaches 14°C there is a 39% \widetilde{P}_x . One step higher (T_{soil} of 17°C), \widetilde{P}_x increases to 52% . This means that the impact of T_{soil} rising from 14 to 17°C increases \widetilde{P}_x by 33% . Moreover, it is apparent that an increase of T_{soil} from 17 to 20°C demonstrates no significant change in Rs , which verifies the tipping point at $\sim 18^{\circ}\text{C}$, as previously mentioned. Therefore, an increase in T_{soil} beyond a certain limit yields a smaller \widetilde{P}_x . For instance, at T_{soil} values of 20 and 23°C

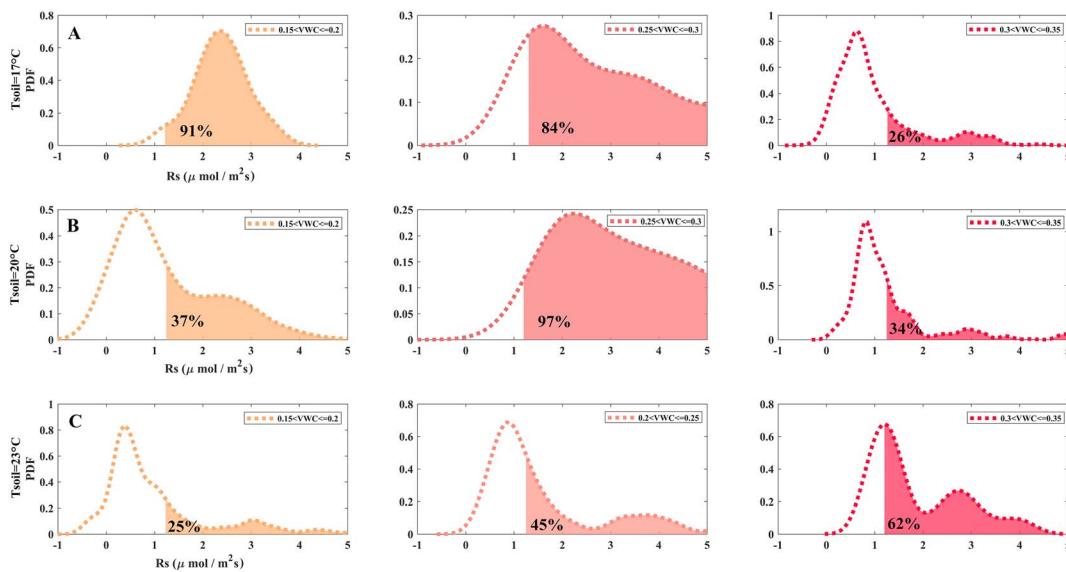


Figure 6. Conditional probability density functions (PDFs) of Rs given T_{soil} values of 17, 20, and 23 °C and volumetric water content (VWC) values ranging with 0.05- m^3/m^3 step sizes. The shaded area marks the probability of exceeding annual mean of Rs . Some VWC ranges are excluded from the panels due to lack of data or insufficient data points at given T_{soil} values (see section 2). For instance, we present VWC ranges (0.20 – $0.25 \text{ m}^3/\text{m}^3$) for $T_{\text{soil}} 23$ °C (row c, middle) instead of VWC ranges between 0.25 and $0.30 \text{ m}^3/\text{m}^3$ due to insufficient observation data under the same T_{soil} conditions.

(Figure 5b), $\widetilde{P_x}$ steps down by 35% (from 49% to 32%). Interestingly, the mode (most likely value) of the PDFs decrease as we condition on higher T_{soil} values.

In Figure 6 we take VWC into account as an additional covariate affecting Rs , to calculate the conditional PDF. In this figure, the shaded area in the panels shows $\widetilde{P_{x,z}}$ (equation (5)) at the given T_{soil} values (17, 20, and 23 °C) and VWC values ranging between 0.15 and $0.40 \text{ m}^3/\text{m}^3$ with a step size of $0.05 \text{ m}^3/\text{m}^3$. Furthermore, some VWC ranges are excluded from the panels in Figure 6 due to either lack of data or insufficient data points (see section 2) at the given T_{soil} values. For example, we did not have sufficient observations for VWC ranges between 0.25 and $0.30 \text{ m}^3/\text{m}^3$ for T_{soil} at 23 °C, and hence, no result is reported. However, we did have sufficient data points for VWC ranges 0.20 – $0.25 \text{ m}^3/\text{m}^3$ under the same T_{soil} conditions, and the results are presented in its place (Figure 6c, middle). Row (a) shows that when T_{soil} reaches 17 °C, the mode of the Rs distribution shifts to lower Rs rates, as VWC rises. Therefore, the chance that Rs goes beyond the annual mean ($\widetilde{P_{x,z}}$) with rising VWC reduces from 94% to 84% and then to 26%. Row (b) shows that the impact of rising VWC conditioned on T_{soil} at 17 °C reduces $\widetilde{P_{x,z}}$ by 71%. This supports our findings that in lower T_{soil} values, an increase in VWC corresponds with decreasing Rs rates. However, with an increase in T_{soil} and VWC this relationship reverses. In row (c), we observe that the mode of Rs shifts to higher values, with increasing VWC. Thus, $\widetilde{P_{x,z}}$ increases by 148% (from 25% to 62%). It is worth noting the mode of the Rs distribution shifts significantly to lower values with increasing T_{soil} , as shown in column 1 (VWC < $0.20 \text{ m}^3/\text{m}^3$). $\widetilde{P_{x,z}}$ declines from 91% to 25% with increasing T_{soil} . Interestingly, the third column (VWC > $0.30 \text{ m}^3/\text{m}^3$) portrays that the mode of Rs shifts higher with increasing T_{soil} . Consequently, $\widetilde{P_{x,z}}$ increases by a factor of 1.38, from 26% to 62%.

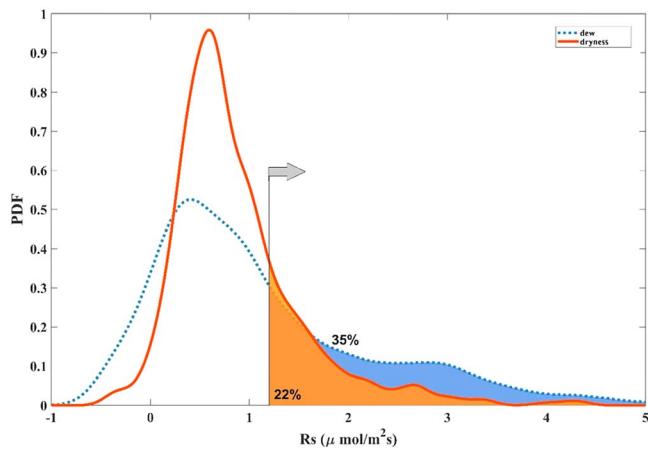


Figure 7. Conditional probability density functions (PDFs) of Rs under dryness shows the chance of exceeding annual mean of Rs .

3.5. An Overlooked Source of Moisture

Even though no precipitation events occurred during the dry season, we observed random Rs increases in various magnitudes and durations, especially from June onward. Rs is mainly controlled by T_{soil}

and VWC, and since T_{soil} is sufficiently available, we hypothesize that an overlooked source of moisture other than precipitation is influencing Rs . Various mechanisms (e.g., fog, dew, and water vapor adsorption) have been discussed to explain how water, besides precipitation, infiltrates soil's surface layer (Agam & Berliner, 2006; Beysens, 1995; McHugh et al., 2015). Several studies have suggested that dew is an important source of water in drylands, including arid and semiarid areas (Malek et al., 1999; McHugh et al., 2015; Shen et al., 2008). Dew is generally formed when T_{soil} surface is lower than or equal to T_{dew} , during which water vapor from the air in contact with the cold soil surface condenses in dew (Agam & Berliner, 2006; Beysens, 1995). The resulting condensed water then seeps into the soil and stimulates roots and microbial activity (Escolar et al., 2015).

The PD (equation (6)) of night air T_{cham} and night T_{soil} surface shows only a ~5% discrepancy. This leads to the conclusion that T_{soil} surface matches with the air T_{cham} during the night. We, therefore, use the min values of the air chamber temperature to identify time periods where T_{soil} surface is lower than dew point temperature (T_{dew}) indicating dew formation. Figure 7 displays the PDF of Rs conditioned on dryness (T_{soil} surface $> T_{dew}$) and dew (T_{soil} surface $\leq T_{dew}$). The shaded area displays \tilde{P}_x (equation (4)) equal to 22% and 35% given dryness and dew, respectively. This means that the presence of dew causes an increase of \tilde{P}_x by 60%. Thus, the process of absorption of water vapor into the soil surface has the potential to be a crucial contributor to the carbon cycling in semiarid areas. Our result compatible with previous studies show dew is a main factor besides T_{soil} and VWC for assessing Rs in dry seasons (Escolar et al., 2015; Jacobson et al., 2015; McHugh et al., 2015; Wang et al., 2014).

4. Conclusion

Soil respiration (Rs) is a critical component of the carbon cycle and peculiarly sensitive to climate variability. We use a probabilistic model to describe the change in the entire Rs distribution under various hydroclimatic conditions. We analyze and characterize measured high-frequency data of Rs on bare soil to enhance our understanding of the temporal Rs dynamics. We use subhourly records of Rs and other parameters from February 2016 to February 2017 obtained in a semiarid ecosystem in Southern California. Rs follows a similar Gaussian pattern with increasing soil temperature (T_{soil}). Rate of Rs increases below ~18 °C, decreases up to ~27 °C, and shows almost no response beyond ~27 °C, with increasing T_{soil} . We use the probabilistic model to assess both the increasing and decreasing response of Rs with increasing T_{soil} . We have selected two ranges with step sizes of 3 °C where Rs show opposing responses. When T_{soil} increases from 14 to 17 °C the probability of exceeding annual mean of Rs (1.2 $\mu\text{mol CO}_2/\text{m}^2\text{s}$) increases by 33%. Furthermore, we show that with increasing T_{soil} from 20 to 23 °C the probability of exceeding the annual mean of Rs declines by 35%. By considering VWC in conjunction with T_{soil} in the probabilistic model, we reveal that increasing VWC at lower temperatures (e.g., 17 °C) decreases the probability of exceeding annual mean of Rs . However, this characteristic changes with increasing T_{soil} ; higher values of T_{soil} (e.g., 23 °C) result in an increase in the probability of exceeding annual mean of Rs , with rising VWC. Furthermore, we display that during dew the probability of exceeding the annual mean of Rs could increase up to 60%. Overall, we show that by using the probabilistic model, we gain information on the entire distribution of the reaction of Rs with changing T_{soil} and VWC; we assess the impacts of changes in T_{soil} and VWC on Rs . The proposed model allows detecting changes in the Rs distribution due to shifts in hydroclimatic drivers such as T_{soil} and VWC. The method is general and can be applied to different applications and variables.

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