Environmental Research Letters

LETTER

ENSO-driven reverse coupling in interannual variability of pantropical water availability and global atmospheric CO₂ growth rate

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Keywords: ENSO, climate-carbon coupling, microwave remote sensing, water availability

Supplementary material for this article is available online

Abstract

The large interannual variability of global atmospheric CO₂ growth rate originates primarily from variation in carbon dioxide (CO₂) uptake of pantropical terrestrial ecosystems, which covaries with the El Niño–Southern Oscillation (ENSO) modulated climate fluctuations of water availability and temperature change. However, the role of ENSO in modulating the contributions of regional to overall water availability interannual variability, and the phase and strength of water availability-CO₂ coupling remain poorly constrained across functionally diverse pantropical terrestrial ecosystems. Using satellite microwave and ground water availability and well-mixed global atmospheric CO₂ concentration observations, the coupling in interannual variability of water availability-CO₂ and their relationship with ENSO was investigated from 1998 to 2016. The results demonstrated causal sequence of ENSO, water availability, and global atmospheric CO₂ growth rate, the phase and magnitude of water availability-CO₂ coupling was primarily determined by phase and strength of correlation between ENSO and water availability, revealing ENSO-driven robust and reverse coupling of water availability-CO₂. Moreover, tropical rainforests, savannas, and shrublands dominated the pantropical water availability variations and showed stronger coupling strength. Therefore, the strong interannual variability of atmospheric CO₂ growth rate originates from ENSO-driven frequent variations of water availability and the subsequently concurrent carbon uptake over pantropical rainforests, savannas, and shrublands. The findings provided new insights to understand and predict interannual variability of water availability and CO₂ growth rate based on ENSO and its predictability.

1. Introduction

The large interannual variability (IAV) of global atmospheric carbon dioxide (CO₂) growth rate originates primarily from variations in CO₂ uptake by pantropical terrestrial ecosystems, whose carbon balance is basically controlled by climate fluctuations of water availability and heat stress related to precipitation and temperature anomalies (Beer et al 2010, Ballantyne et al 2012, Ahlström et al 2015, Liu et al 2015, Jung et al 2017). The climate IAV is supposed to be modulated by the El Niño–Southern Oscillation (ENSO) cycle, the most prominent natural climate phenomena on interannual time scale with global impacts (McPhaden et al 2006). Previous studies have implied significant correlations among ENSO, climate, and global atmospheric carbon dioxide (CO₂) growth rate, showing an overall dry and warm/wet and cool climate during El Niño/La Niña, followed by high/low atmospheric CO₂ growth rate (Nemani et al 2003, Ahlström et al 2015).

The relationships of ENSO-climate-CO₂ have been used to forecast drought changes (Dai 2012, Yuan and Wood 2013), as well as to predict global atmospheric CO₂ concentration based on ENSO evolution (Bettis et al 2016). Strong and robust coupling
between IAV of ENSO, tropical land temperature anomaly, and atmospheric CO2 growth rate has been well verified (Braswell et al 1997, Wang et al 2013), and it provides a benchmark for constrain of tropical carbon sensitivity to temperature anomaly under climate change (Cox et al 2013, Wenzel et al 2014). Water availability is the dominant driver of the local IAV in terrestrial carbon balance components of gross primary productivity and ecosystem respiration (Jung et al 2017). Consequently, the robustness in coupling of water availability-CO2 as well as their connections with ENSO are crucial to effectively exploit ENSO’s predictability to forecast variations of climate and carbon cycles. However, the phase and magnitude in coupling robustness and the timing of the responses of water availability to ENSO and atmospheric CO2 growth rate to water availability remain poorly constrained across functionally diverse pantropical terrestrial ecosystems.

Better understandings of coupling characteristics require reliable high-quality water availability observations from both satellite remote sensing and ground meteorological station. Basing on the long-term ground climate observations, the standardized precipitation index (SPI) and self-calibrating Palmer drought severity index (scPDSI), have been widely used in detection of water availability variations (McKee et al 1993, Wells et al 2004, van der Schrier et al 2013). It should be note that the accuracies in spatial-temporal changes of water availability as monitored by SPI and scPDSI are to some extent hampered by the relatively coarse distributions of the available ground weather stations particularly over tropics (Beck et al 2017). Furthermore, the microwave integrated drought index (MIDI) provides reliable water availability observations in high spatial and temporal resolution by integrating state-of-the-art satellite microwave derived precipitation, land surface soil moisture (few centimeters below land surface) and temperature together (Zhang and Jia 2013, Zhang et al 2019). In addition, it works in all-weather condition and withstands the adverse impacts of high cloud cover or atmospheric aerosols concentration on remote sensing observations, which is critically important over the pantropical regions (Stubenrauch et al 2013, Reddington et al 2017).

Previous studies have demonstrated that climatically and functionally diverse pantropical terrestrial ecosystems (biomes) play different roles, the tropical rainforests are important for global biodiversity, water cycle, and mean carbon sink; while shrublands and savannas dominate trend and IAV of land CO2 uptake (Beer et al 2010, Jung et al 2010, Poulter et al 2014, Ahlström et al 2015). Furthermore, the impacts of water availability on ecosystem are biome dependent (Reichstein et al 2013), and therefore coupling features of water availability-CO2 and their connection strength and response timing to ENSO across biomes must be better understood in order to assess climate variation and associated ecosystem responses to ENSO cycle (Nemani et al 2003). Improving the understandings require better knowledge of regional roles in governing overall water availability IAV, however, the relative contributions of regional to overall water availability IAV are not well characterized over pantropical regions. Although previous studies have assessed the connections of ENSO-climate-CO2 (Wang et al 2013, Ahlström et al 2015), the role of ENSO in modulating the water availability contributions and the water availability-CO2 coupling robustness are not well known.

In this study, by using high-quality ground and satellite water availability observations and well-mixed global atmospheric CO2 concentration measurements, rigorous analysis is performed to investigate the regulations of ENSO on coupling robustness in IAV of pantropical water availability and global atmospheric CO2 growth rate across climatically and functionally diverse pantropical terrestrial ecosystems. We start investigating the spatial-temporal connections of ENSO-water availability-CO2 based on cross correlation analyses among monthly multivariate ENSO index (MEI), MIDI/SPI/scPDSI, and global atmospheric CO2 growth rate. We further allocate the relative contributions of region to the overall water availability IAV, and finally the phase and magnitude in coupling robustness as well as the role of ENSO in the coupling are evaluated.

2. Data and methods

Multi-source monthly satellite and ground observartion data over pantropical regions (38.5°S–38.5°N) at spatial resolution of 0.25° from 1998 to 2016 were used in this study (table S1 is available online at stacks.iop.org/ERL/15/034006/mmedia).

2.1. The ENSO index and the global mean atmospheric CO2 growth rate

The MEI was employed to detect characteristics of ENSO (Wolter and Timlin 1998), which fluctuates between warm (El Niño) and cold (La Niña) conditions in the tropical Pacific. Globally monthly mean surface atmospheric CO2 concentration is based on measurements of well-mixed marine boundary layer air from the Cooperative Global Air Sampling Network by the Global Monitoring Division of NOAA/Earth System Research Laboratory (Conway et al 1994). The annual CO2 growth rate at monthly time step is the difference in concentration (ppm) of the same month between the adjacent two years (e.g. growth rate for January of 2011 is calculated by the CO2 concentration in January of 2011 subtracts the value in January of 2010).
2.2. Biome classification

Seven climatically and functionally diverse biomes were derived by the majority class within each grid in 0.25° spatial resolution based on the Climate Modeling Grid land cover with International Geosphere Biosphere Program classification (2012 MCD12C1 051) (Friedli et al. 2010), including tropical rainforests, subtropical forests, shrublands, savannas, grasslands, croplands, and sparsely vegetated (figure S1).

2.3. Water availability detected by satellite- and ground-based drought indices

2.3.1. Ground-based indices

The latest accessible Climate Research Unit dataset (CRU TS 4.03) provides gridded global land monthly climatic observations at spatial resolution of 0.5° (interpolated from ground meteorological station observations) from 1901 to 2018 (Harris et al. 2014). The one-month SPI was calculated based on the long-term CRU precipitation records (McKee et al. 1993). The monthly scPDSI, which accounts for both effects of precipitation and potential evapotranspiration on water availability (Wells et al. 2004), was also calculated for the period 1901–2018 based on the CRU TS 4.03 dataset (van der Schrier et al. 2013). The SPI and scPDSI datasets were interpolated to 0.25° using the nearest neighbor sampling methods.

2.3.2. Satellite-based MIDI

The MIDI integrates the precipitation condition index (PCI), the soil moisture condition index (SMCI), and the temperature condition index (TCI), providing spatially homogeneous and temporally continuous of water availability observations (Zhang and Jia 2013). The PCI, SMCI, and TCI are linear normalized from 0 to 1, and they relatively represent dry to wet climate based on satellite remotely sensed precipitation, soil moisture, and land surface temperature. Here, the ensemble average of PCI from five widely used satellite derived precipitation datasets (Joyce et al. 2004, Huffman et al. 2007, Ashouri et al. 2015, Funk et al. 2015, Beck et al. 2017) were ultimately employed due to its improved capability than individual precipitation-based PCI in drought monitoring (Zhang et al. 2019).

The SMCI was calculated based on merged dataset v04.2 of Climate Change Initiative soil moisture dataset. Which was developed by the European Space Agency based on both passive and active microwave observations, provides reliable performances in assessing land surface moisture changes over sparse to moderate vegetated areas (Liu et al. 2011, 2012, Wagner et al. 2012), and has been extensively used in Earth system science (Dorigo et al. 2017).

The night time land surface temperature (LST) dataset derived by the land parameter retrieval model from passive satellite microwave sensors of the Tropical Rainfall Measuring Mission Microwave Imager (TMI) and Advanced Microwave Scanning Radiometer 2 (AMSR2) were retrieved to denote the thermal changes (Owe et al. 2008, Holmes et al. 2009). The mean LST anomalies of TMI and AMSR2 were derived to calculate the TCI. In order to ensure full spatial-temporal coverage of the MIDI over the pantropical regions, four combination constitutions were complementarily used as suggested according to data quality and availability of soil moisture and LST (table S2) (Zhang and Jia 2013, Zhang et al. 2019).

2.4. Identify coupling robustness

The IAV of ENSO, water availability, and atmospheric CO₂ growth rate was extracted using the ensemble empirical mode decomposition (EEMD), a noise-assisted, adaptive, and temporal local analysis method (Wu and Huang 2011). The noise added to data analysis is with amplitude of 0.20 standard deviation, and the ensemble number is 1000 as recommended. Variations with time scales greater than 1.5 years were summed to represent IAV (figure S2). The EEMD IAV effectively eliminates short-term (high frequency) and long-term (trend) signal disturbances on IAV. The relative contributions of regions/biomes to overall water availability IAV were estimated followed the method as proposed in Ahlström et al. (2015). Pixels with high positive values govern the overall water availability IAV, while pixels with negative values weaken global IAV; hence, global IAV would be greater if these pixels in negative value were excluded.

The cross-Spearman correlation analysis was conducted to assess the sequent connection among ENSO, water availability, and atmospheric CO₂ growth rate in space and time. It measures monotonic relationship between two variables based on ranks, and resistant to effects of outliers (Helsel and Hirsch 2002). P value of 0.05 is used to test significance. The absolute maximum correlation (peak correlation: R) and lagged time (month which held the peak correlation) were further obtained. Finally, the coupling robustness was calculated by the contribution (C) times the correlation (R), and therefore regions with greater absolute values possess stronger coupling strength, while negative values mean opposite coupling phases between water availability and ENSO/atmospheric CO₂ growth rate.

3. Results and discussions

3.1. Causal sequence of ENSO-water availability-CO₂

The spatial distributions of peak correlation coefficient between water availability (MIDI) and ENSO/atmospheric CO₂ growth rate were identical, showing dominant negative correlation (71.4%/70.9%) especially over tropics and the subtropical Southern Hemisphere; whereas positive correlation (26.6%/28.1%) mainly distributed in 20°N northward (figures 1(a), (b)). The lagged response time of water availability to
ENSO was mixed in space, 59% of areas had the peak correlation within ±5 lagged months, with faster responses over Australia, tropical America and Asia (figure 1(c)). Furthermore, delayed responses of atmospheric CO2 growth rate to water availability change covered majority regions (67.8%) (figure 1(d)). The spatial-temporal connections of SPI/scPDSI and ENSO/CO2 showed principally consistent characteristics as that between MIDI and ENSO/CO2 (figure S3). Moreover, the SPI had the largest percentage in positive correlations with ENSO/CO2 (43.3%/43.8%), followed by the scPDSI (35.5%/39.6%) and the MIDI (26.6%/28.1%), presenting decreased heterogeneity in correlations.

The IAV of water availability fluctuated considerably and generally showed similar temporal changes as indicated by the MIDI, SPI, and scPDSI (figure 2). The phases and magnitude for water availability of different pixels would counteract or strengthen the overall IAV of regions, biomes, and the whole study region. The overall water availability was steadily increased until 1999 during and after La Niña, which mainly occurred over tropical rainforests, shrublands, and savannas. A rebound occurred around 2003 in particular over subtropical forests, shrublands, grasslands, croplands, and sparsely vegetated, following by a fast decrease associated with El Niño until 2005. Then water stress gradually released and reached the wettest condition in 2011 with responses to a strong La Niña event over tropical rainforests, shrublands, savannas, and croplands, and therefore provided abundant water and inducing exceptional terrestrial carbon sink in particular over Africa and Australia, consequently followed by lower CO2 growth rate (Bastos et al 2013, Poulter et al 2014). Whereas strong El Niño in 2015/2016 brought severe water deficits especially over Amazon rainforests and southern Africa savannas (Jiménez-Muñoz et al 2016), accompanied by a quick rise of CO2 growth rate (Chatterjee et al 2017).

The spatial-temporal correlation patterns (strength and lagged time) of ENSO-water availability-CO2 showed were the overall characteristics for pixel/biome over the whole study time period. Taking the pantropical regions as a whole, its water availability (MIDI/ SPI/scPDSI, hereafter in the same order) exhibited near real-time responses to ENSO (lag = 1/3/0, figures 3(a)–(c)), and led the changes of CO2 growth rate about nine months (median value and the same hereafter; lag = 9/11/8, figures 3(d)–(f)). It showed obvious difference in correlations with ENSO, the MIDI had the strongest $R$ (~0.79), followed by the scPDSI (~0.65) and the SPI (~0.52). While water availability explained similarly for CO2 variance (41% and 44%).

Biome water availability showed diverse connections with ENSO/CO2 (figure 3). Tropical rainforests had the most robust chained connections of ENSO-water availability-CO2, and presented the strongest and most homogeneous negative correlation in space with fast responses time to ENSO (2/0/2; figures 3(a)–(c)), and led the atmospheric CO2 concentration changes about ten months (10/12/9; figures 3(d)–(f)). ENSO explained about 77% ($R^2 = 0.79/0.74/0.77$) of the variance of tropical rainforests water availability, and they had the strongest explanation ($R^2 = 0.52/0.69/0.52$) of variance of CO2 growth rate among biomes (figure 3).

The correlation robustness of water availability-CO2 for savannas was weaker than that of tropical rainforests but stronger than other biomes. This may be related to the different responses of vegetation to water availability variations across biomes. The rainforests are vulnerable to water availability, in particular the droughts. The impacts of droughts on the carbon balance in forests are both immediate and potentially long-lasting, and the recovery of plant regrowth takes long time. In contrast,
although the savannas are susceptible to droughts, however, they have high resilience to water stress and high recovery potential as water availability change (Reichstein et al. 2013).

ENSO led water availability IAV about five months, while CO₂ lagged with the shortest time with six months to water availability (figure 3). Shrublands in the Southern Hemisphere mainly possessed significant negative correlations, in contrast significant positive correlations distributed over the Northern Hemisphere (figures 1 and S3); thus, offsetting and reducing the overall correlation strength with ENSO/CO₂ as a biome. However, water availability indicated by SPI/scPDSI for subtropical forests and grasslands presented stronger positive correlations with ENSO than that by MIDI.

MIDI had greater areas with higher correlation (correlation difference greater than 0) and stronger negative correlation than SPI/scPDSI in space (figure S4), and they basically distributed over tropical

Figure 2. Temporal changes of interannual variability for ENSO (violet line), atmospheric CO₂ growth rate (wine line), and water availability (MIDI: black line, SPI: blue line, scPDSI: olive line) from 1998 to 2016. The black horizontal line indicates the zero-crossing value for each biome.
regions, where the strongest carbon and water cycle occur. In contrast, the SPI/scPDSI had higher correlation in the subtropics (figure S5). In addition, the MIDI showed an overall positive correlation anomaly (colored numbers in figure S5). The comparison results demonstrated an overall stronger correlation in the ENSO-water availability-CO$_2$ as indicated by the MIDI than the SPI/scPDSI did.

The correlation strength and lagged time of water availability to ENSO is closely related to diverse teleconnection patterns and corresponding weather and climate impacts. When sea surface temperature (SST) changes in the tropical Pacific, atmosphere circulations over regions tropical Pacific and bordering areas respond directly to SST forcing and show a strong correlation with a short time lag (McPhaden et al 2006). On the other hand, the SST change shifts the atmospheric deep convection and adjusts the global Walker circulation. Then, it excites Rossby wave trains that propagate into extratropics, generating

Figure 3. Cross-correlations of interannual variability among ENSO, water availability (MIDI, SPI, and scPDSI), and atmospheric CO$_2$ growth rate across biomes. The peak correlation and corresponding lagged month are enclosed in the parentheses. Significance levels ($p > 0.05$) are shown between the gray horizontal dashed line.
changes to westerlies and interfering with regional modes of climate variability, and finally affects the precipitation and temperatures patterns (Cai et al 2015, Timmermann et al 2018). Noticeably, the amplitude/work time of ENSO SST anomalies forcing on the regional atmospheric circulation determines the regional connection strength/lagged time of water availability to ENSO, where the middle latitude regions showed a low correlation strength and long lagged time than tropics.

The IAV of CO$_2$ growth rate primarily originates from variations of pantropical terrestrial carbon budget (Zeng et al 2005), and the degree of covariation between local and overall terrestrial carbon budget determines the connection robustness between regional ecosystem and global atmospheric CO$_2$ growth rate. Water availability is the dominant driver of local IAV in carbon budget (Jung et al 2017). Therefore, the correlation between water availability and CO$_2$ growth rate is associated with the water-driven IAV of terrestrial carbon balance. Accordingly, the higher correlation occurs over the regions of tropical rainforests, savannas, and shrublands who dominate the IAV of global terrestrial carbon budget (Ahlstrom et al 2015).

There is a time lag between regional land carbon fluxes and the global mean CO$_2$ concentration of well-mixed marine boundary layer (Conway et al 1994). The potential processes governing the lagged time of CO$_2$ growth to water availability were complicated, and were mainly related to water availability sensitivity of different biomes (Vicente-Serrano et al 2013), the CO$_2$ exchange processes through convection at the land surface, and transport processes of CO$_2$ within the atmosphere through atmospheric circulation (Krol et al 2018). The CO$_2$ growth rate is the global mean value of the observation network, and it is not a point observation, moreover the vertical mixing of air in the troposphere and transport time scales varies in different global transport models (Krol et al 2018). Consequently, the exact absolute lagged time of the global mean CO$_2$ growth rate to regional water availability is difficult to determine.

Atmospheres in the tropics and subtropics have vigorous convection and are quickly mixed through a large volume of air associated with Walker and Hadley circulation (Krol et al 2018, Schuh et al 2019). Furthermore, except the deep inland areas, most of the pantropical lands are close to the marine atmosphere. Thus, the relative lagged time should be regulated dominantly by the sensitivity of vegetation to water availability across biomes. Plant in humid biomes like tropical rainforests and subtropical forests are sensitive and respond fast to water changes. Therefore, the CO$_2$ growth rate show a relative longer time lag to water availability over forests than the semi-arid and semi-humid biomes (figures 3(d)–(f)). By contrast, vegetation in semi-arid and semi-humid biomes (shrublands, savannas, and grasslands) are more resistant to water deficits than forests. Thus, they respond to water changes with evident lags, inducing a relative shorter time lag than the forests (Vicente-Serrano et al 2013).

It should be noted that lagged time is decided as the month which held the peak correlation; thus, the line shape of cross-correlations would essentially influence the lagged time. The lagged time would have a greater difference when the cross-correlations show slightly different values at the two peaks in both positive and negative. The correlation values have tiny disparities around the peak correlation and the closest two correlations, a value of correlation difference of 0.016 would bring a two-month lagged time change (figure S6). Additionally, the SPI and scPDSI accounted for the effects of precipitation or temperature (potential evapotranspiration) on water availability; however, the MIDI indicates water availability from both precipitation, soil moisture, and temperature. Therefore, the water availability derived from the three indicators are not the same, and induces differences in the time lags. Here, the lagged month should be interpreted as relative response time instead of the absolute numbers of the lagged month.

ENSO delayed the water availability changes in the eastern Australia (figures 1(c), S3(e) and (g)); however, the correlations between MIDI/SPI/scPDSI and ENSO were strong in the zero lagged month, but the slightly increased correlation strength in subsequent positive lagged months resulted in a longer lagged time, therefore, the regional water availability should be interpreted as coinciding or responding quickly to ENSO.

The different response of rainforests with positive correlation, in contrast to the rest rainforests (negative correlation) in the western Amazon, was both detected by the SPI/scPDSI/MIDI (figures 1 and S3); while difference reflected by the SPI and scPDSI was greater than the MIDI had, resulting from distinct data sources. This characteristic would be possibly related to the regional hydrological cycle, atmospheric circulation pattern, and vegetation resilience. The oceanic moisture inflow of Amazon rainforests mainly comes from the Atlantic Ocean, and the moisture source for rainfall in the western rainforest is more from vegetation evapotranspiration instead of oceanic inflow (Zemp et al 2017). The evapotranspiration is associated with the deep atmospheric convection, which both affect and respond to the global Hadley and Walker circulations (Barichivich et al 2018). Consequently, the distinct regional hydrological cycle and atmospheric circulation induced diverse responses in the western Amazon rainforests. The northwestern Amazon rainforests have the highest annual precipitation and the highest vegetation resilience among Amazon rainforests (Zemp et al 2017), meaning those rainforests are less sensitive to water availability changes, together with the different atmospheric circulation, inducing a difference in lagged time.
In general, we found a clear causal sequence of ENSO-water availability-CO$_2$ with dominant negative correlations between water availability and ENSO/CO$_2$. The overall negative correlations demonstrated enhanced drought (generally accompanied with high temperature), increased fire activities and plant mortality, and decreased terrestrial ecosystem CO$_2$ uptake during or after El Niño, and led to accelerated rise of atmospheric CO$_2$ concentration (Nemani et al. 2003, Beer et al. 2010, Ahlström et al. 2015). The La Niña condition brings excessive wetness and increased terrestrial ecosystem CO$_2$ uptake especially over northeastern and northwestern south America, rainforests in Africa, southern Africa, tropical Asia, and northern and eastern Australia (Lyon and Barnston 2005, Dai 2012), and subsequently follows by lower growth rate in atmospheric CO$_2$ concentration (Bastos et al. 2013, Poulter et al. 2014). The opposite correlations (positive versus negative) dampened the overall water availability fluctuation intensity, reducing the overall risk of drought induced carbon release by counteracting effects from opposing correlated regions (wet climate and carbon uptake) to ENSO at a certain time. However, the compensatory regions covered less area and could not overturn the dominant negative correlations with ENSO/CO$_2$.

Previous studies revealed that the teleconnection patterns of ENSO and water availability are complex and not constant in space and time, tightly associated with the space-time complexity of ENSO (McPhaden et al. 2006, Timmermann et al. 2018). While the teleconnections with the tropical Pacific regions and bordering areas are most consistent, whereas the middle latitude regions and around other ocean basin are less consistent. Thus, the regional responses of water availability to diverse spatial-temporal ENSO patterns resulted in time-varying impacts on the global terrestrial carbon budget (Beer et al. 2010, Poulter et al. 2014, Ahlström et al. 2015).

Atmospheric CO$_2$ growth rate is a result of carbon balance between anthropogenic/land use change CO$_2$ emissions and global ocean/land carbon uptake, several processes related to human and natural factors like fire, temperature anomalies, radiation variability, plant mortality, cropland irrigation and management, deforestation, land use changes, and fossil CO$_2$ emissions occurred inside or outside the pantropical regions also altered the global CO$_2$ growth and water availability-CO$_2$ connection patterns (Ballantyne et al. 2012, Wang et al. 2013, Liu et al. 2015, Chatterjee et al. 2017). The synchronous coupling in IAV of ENSO-CO$_2$ are mainly contributed from the responses of pantropical ecosystems to concurrent climate variations (Zeng et al. 2005, Ahlström et al. 2015). Water availability is the overall dominant driver of the local IAV of photosynthesis and respiration (Jung et al. 2017), and the temperature and radiation also play important roles in driving the carbon cycle (Braswell et al. 1997, Wang et al. 2013). Here, the water availability provides an explanation of climate-CO$_2$ coupling, and the water availability works together with temperature and radiation to drive the climate-CO$_2$ cycle. Further investigations are needed to better understand the regional patterns in control of water availability, radiation, and temperature on IAV of terrestrial carbon balance and the role of ENSO.

### 3.2. Tropical rainforests, savannas, and shrublands dominated the water availability IAV

Generally, contribution for IAV of water availability indicated by MIDI/SPI/scPDSI exhibited comparable spatial patterns, presenting predominant positive contribution (75%/65.5%/65.8%) (figures 4(a)–(c)). Regions with positive scores (green shaded), in particular areas with higher scores over northern Latin America, part of central and southern Africa, tropical Asia, and Australia, were suggested to have dominant role in governing the overall IAV. Whereas the Northern Hemisphere subtropics, in particular regions of north America, west and central Asia, had strong negative scores (red shaded), counteracting the overall IAV (figures 4(a)–(c)). The most obvious spatial inconsistency between three indices distributed over southeastern China, where the SPI showed strong negative contribution, by contrast, the MIDI only had limited regions with negative contribution and the contribution was weak, while the contribution patterns of scPDSI were between the SPI and MIDI. Additionally, nearly 90% of pixels of MIDI possessed positive contribution between regions of 0°C–10°C, whereas the values for SPI/scPDSI were about 20% to 30% lower.

In addition to spatial patterns, contribution of MIDI showed a sharp shape with values distributed within ±0.000 04; but the SPI/scPDSI had a flatter shape with larger range (±0.000 09) (inserted within figure 4(c)). The range of contribution value and its percentage along strength may be determined by proportion difference between positive and negative contribution (MIDI: 50%, SPI: 31%, scPDSI: 31.6%). According to the contribution calculation method, the summed value of all pixels equals one (Ahlström et al. 2015); while the proportion difference (MIDI) was larger, weaker negative values were needed to offset positive values. In contrast, the proportion difference of SPI/scPDSI was smaller, the counteracting effects required stronger values and more area with negative contribution, and therefore enlarging the range and showing a flatter shape in histogram distribution.

Tropical rainforests had the highest proportion in positive contribution, followed by savannas, shrublands, and croplands, indicating an increase in contribution differentiation within biome and proportion with offsetting effect. Importantly tropical rainforests, savannas, and shrublands dominated the pantropical water availability IAV (84.3%/91.6%/91% for MIDI/SPI/scPDSI) (figures 4(d)–(f)).
coinciding with their dominant role in global terrestrial carbon cycle (Beer et al 2010, Ahlström et al 2015).

3.3. Robust and reverse coupling of water availability-CO₂

The reverse coupling in phases of contribution (water availability) and correlation (between water availability and CO₂/ENSO) were dominant, presented majority of positive contribution corresponded to negative correlation (MIDI: 66%/68.4%, SPI: 44.1%/46.7%, scPDSI: 52.8%/57.3%; olive shaded areas in figures 5 and S7 and 8), and vice versa (MIDI: 19.5%/20.9%, SPI: 23%/25.7%, scPDSI: 27.2%/27.9%; orange shaded areas figures 5 and S7 and 8). Furthermore, it showed symmetrical and conformal distributions along longitude (MIDI: \( R = -0.84/-0.93 \), SPI: \( R = -0.69/-0.70 \), scPDSI: \( R = -0.78/-0.86 \); orange/blue text in figures 5 and S7, 8) and latitude (MIDI: \( R = -0.94/-0.92 \), SPI: \( R = -0.64/-0.48 \), scPDSI: \( R = -0.77/-0.85 \); orange/blue text in figures 5 and S7, 8).

Moreover, greater absolute values in correlation (dark red or dark green shaded areas in figures 1(a), (b) and S3(a)–(d)) remarkably coincided with higher absolute scores in contribution (dark green or dark red shaded areas in figures 4(a)–(c)). Meanwhile, strong correspondences occurred between regions with lower absolute values in correlation and contribution, inferred robust coupling of water availability-ENSO/CO₂. Demonstrating that the scores of regions to overall water availability IAV contribution were controlled by strength of correlations between ENSO and water availability; in turn, the robustness of regional water availability.
Figure 5. The reverse coupling phases in interannual variability of water availability (MIDI) and atmospheric CO₂ growth rate/ENSO.

(a) Spatial patterns of coupling phases between water availability and atmospheric CO₂ growth rate, the spatial patterns between water availability and ENSO were exactly similar and not shown. Lines of correlation (R) and contribution (C) in (b), (c) are based on zonal mean values. The correlation efficiency between lines of orange/blue and olive are shown as orange/blue texts.

Figure 6. Characteristics in coupling strength between interannual variability of water availability (MIDI) and atmospheric CO₂ growth rate/ENSO. The coupling strength in (a), (b) are calculated by R (correlation between MIDI and atmospheric CO₂ growth rate) times C (water availability contribution), the higher in absolute values, the stronger in coupling strength. Percentage distributions of coupling robustness are insetted in (a).
availability contribution basically determined the correlation between water availability and atmospheric CO$_2$ growth rate.

The water availability-CO$_2$ showed stronger coupling strength (contribution (C) times the correlation (R)) over southeastern United States, Northern South America, tropical rainforests in Africa, Southern Africa, tropical Asia, and Australia (figures 6(a) and S9, 10(a)). Furthermore, stronger coupling robustness was found over tropical rainforests, savannas, and shrublands (figures 6(b) and S9, 10(b)); and the spatial distributions of biomes induced two peaks near equator and 20°S (figures 6(c) and S9, 10(c)). Therefore, the phase and magnitude of coupling robustness of water availability-CO$_2$ were driven by the phase and strength of correlation between ENSO and water availability.

The scPDSI had closer spatial distributions with MIDI in coupling robustness than the SPI did. Patterns of coupling robustness between water availability-ENSO were similar (figures not shown). In addition, the coupling robustness of water availability-ENSO was slightly stronger than strength of water availability-CO$_2$ (figures 6(c) and S9, 10(c)). The MIDI showed more homogeneous coupling robustness than the SPI and scPDSI did, and presented the strongest strength over tropical rainforests located equator (figure 6). Whereas the SPI and scPDSI, in particular the SPI, had more heterogenous distributions in space, and their coupling robustness for shrublands especially over Australia was stronger than that indicated by MIDI (figures S9, 10).

The differences in the coupling characteristics of ENSO-water availability-CO$_2$ among MIDI, SPI, and scPDSI come from two aspects, the different definitions of water availability and the data sources. The CRU dataset is gridded from interpolation of the ground observations, and it provides valuable long-term water availability estimates. However, the ground stations are sparely distributed in the tropics (Harris et al. 2014, Beck et al. 2017). In addition to the ground-based SPI and scPDSI, the MIDI provides satellite-based water availability assessment with high spatial and temporal resolution over heterogeneous tropics in recent years. The MIDI, SPI, and scPDSI worked together and jointly revealed the key role of tropical rainforests, savannas, and shrublands in coupling the ENSO-water availability-CO$_2$.

Tropical rainforests, savannas, and shrublands had stronger coupling robustness, together with their dominant role in IAV of pantropical water availability and global terrestrial carbon cycle (Beer et al. 2010, Poulter et al. 2014, Ahlström et al. 2015), as well as the causal sequence of ENSO-water availability-CO$_2$ (Jung et al. 2017), our findings demonstrated that the strong IAV of atmospheric CO$_2$ growth rate was dominated by ENSO-driven frequent changes of water availability and carbon uptake over pantropical rainforests, savannas, and shrublands.

Overall, our results revealed ENSO-driven robust and reverse coupling of pantropical land water availability and global atmospheric CO$_2$ growth rate based on satellite and ground observation. The findings provided new insights to understand and predict IAV of water availability and CO$_2$ growth rate based on ENSO and its predictability. We emphasize that the ENSO-driven water availability-CO$_2$ coupling provides a robust explanation of coupled climate and carbon cycle, besides the tropical land temperature and CO$_2$ coupling (Braswell et al. 1997, Wang et al. 2013). The findings inherit uncertainties owing to inconsistent teleconnection patterns of regional climate to ENSO complexity (Cai et al. 2015, Timmermann et al. 2018), the responses of vegetation to water availability (Vicente-Serrano et al. 2013), as well as the complex natural and human involved global carbon cycle (Ballantyne et al. 2012, Chatterjee et al. 2017, Jung et al. 2017).

4. Conclusions

This study assessed the spatial and temporal coupling of ENSO, pantropical water availability, and global atmospheric CO$_2$ growth rate based on satellite and ground observations. A clear causal sequence of ENSO-water availability-CO$_2$ with dominant negative correlations between water availability and ENSO/CO$_2$ was found. The scores of regions to overall water availability IAV contribution were controlled by strength of correlations between ENSO and water availability; in turn, the robustness of regional water availability contribution basically determined the correlation between water availability and CO$_2$ growth rate. The results demonstrated robust and reverse coupling of pantropical land water availability and global atmospheric CO$_2$ growth rate in terms of IAV, more importantly the phase and magnitude of coupling robustness was driven by the phase and strength of correlation between ENSO and water availability.

Tropical rainforests, savannas, and shrublands had stronger coupling robustness and showed two peaks in strength near equator and 20°S, together with their dominant role in IAV of pantropical water availability and global terrestrial carbon cycle, demonstrating that the strong IAV of atmospheric CO$_2$ growth rate originates from ENSO-driven frequent variations of water availability and the subsequently concurrent carbon uptake over pantropical rainforests, savannas, and shrublands. The heterogeneous patterns in connections of ENSO-water availability-CO$_2$ helped to maintain stability of global water availability and atmospheric CO$_2$ growth rate according to compensatory effects in space and time. The ENSO-driven coupling provided new insights to understand and predict IAV of water availability and CO$_2$ growth rate based on ENSO and its predictability.
Achnowledgments

This work was jointly supported by the Strategic Priority Research Program of the Chinese Academy of Sciences (Grant No. XDA19030401) and the National Natural Science Foundation of China (Grant No. 41590853 and 41305106). All data used in this study are publicly accessible (table S1).

Data availability statements

The data that support the findings of this study are openly available at DOI https://doi.org/10.25412/iop.11429904.v1.

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