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Key Points:

- The 2019 extreme positive Indian Ocean Dipole caused the enhanced land carbon uptake over India-Africa and release over Asia-Pacific during September–December
- These regional net biome productivity (NBP) anomalies were closely related to soil moisture variations with a dominant role of gross primary productivity
- These Indian Ocean Dipole-induced regional NBP anomalies showed comparable magnitudes but different patterns to those following the 2015 extreme El Niño

Supporting Information:

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

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Enhanced India-Africa Carbon Uptake and Asia-Pacific Carbon Release Associated With the 2019 Extreme Positive Indian Ocean Dipole

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Abstract The 2019 extreme positive Indian Ocean dipole drove climate extremes over Indian Ocean rim countries with unclear carbon-cycle responses. We investigated its impact on net biome productivity (NBP) and its constituent fluxes, using the Global Carbon Assimilation System (GCASv2) product, process-based model simulations from TRENDYv9, and satellite-based gross primary productivity (GPP). By distinguishing two separate regions, the India-Africa and Asia-Pacific, GCASv2 indicated enhanced terrestrial carbon uptake of 0.23 ± 0.20 PgC and release of 0.38 ± 0.15 PgC, respectively, during September–December (SOND) 2019. These NBP anomalies had comparable magnitudes to those following the 2015 extreme El Niño which, however, caused the consistent carbon release in both regions. The TRENDYv9 model ensemble confirmed these NBP responses, albeit with smaller magnitudes. These regional NBP anomalies were related to soil moisture variations with a dominant role of GPP. Understanding the impact of IOD provides new insights into mechanisms driving interannual variations in regional carbon cycling.

Plain Language Summary The extreme Indian Ocean Dipole (IOD) can drive climate extremes, such as floods, heatwaves, droughts, and wildfires, over the Indian Ocean rim countries. However, responses of regional terrestrial carbon cycling to IOD remained unclear. We used the net biome productivity (NBP) from an atmospheric inversion and multiple terrestrial biosphere models to demonstrate an enhanced terrestrial carbon uptake and release over the India-Africa and Asia-Pacific regions, respectively, during the extreme positive IOD (September–December) in 2019. These IOD-induced regional NBP anomalies showed comparable magnitudes but different patterns to those following the 2015 extreme El Niño. Along with the more frequent extreme IOD under future greenhouse warming, IOD will be an important mechanism driving interannual variations in regional carbon cycling.

1. Introduction

The Indian Ocean Dipole (IOD) is an ocean-atmosphere coupled mode of variability that can directly influence climate variations on interannual timescales over the regions surrounding the Indian Ocean (Ashok et al., 2004; Behera et al., 2006; Cai et al., 2011; Saji & Yamagata, 2003; Saji et al., 1999). The climate impacts of IOD are known to be different from those induced by the El Niño-Southern Oscillation (ENSO) (Ashok et al., 2004; Cai et al., 2011; Saji & Yamagata, 2003). In a positive IOD (denoted as “pIOD”), the sea surface temperature (SST) initially cools off Sumatra-Java, enhancing the southeasterly trade winds. The anomalous southeasterly winds in turn reinforce the initial cooling through the enhanced upwelling and shoaling of the thermocline but accumulate the warm SST over the equatorial western Indian Ocean (Saji et al., 1999). These altered circulations in the ocean and atmosphere can cause climate extremes, such as floods, heatwaves, droughts, and wildfires (Ashok et al., 2003; Behera et al., 2005; Cai et al., 2009; Kim et al., 2019; Ummenhofer et al., 2009), over the Indian Ocean rim countries (IORC), exerting the concurrent and lagged abiotic stresses on regional ecosystems and terrestrial carbon fluxes.

More recently, an extreme pIOD event, one of the strongest in the last four decades, occurred in 2019 (Figure S1 in Supporting Information S1). It contributed to the megabushfires over the temperate forests in eastern Australia, releasing large amounts of carbon dioxide (CO₂) (Boer et al., 2020; Byrne et al., 2021; van der Velde et al., 2021; Wang et al., 2020). Concurrently, the Niño 3.4 index in 2019 barely satisfied the criterion for El Niño (Figure S1 in Supporting Information S1). Hence the 2019 extreme pIOD event is a unique case that allows for the separation of the impact of the pIOD on the terrestrial carbon cycle from other atmospheric modes affecting the IORC in the carbon satellite era.

The impact of the IOD on the terrestrial carbon cycle is not well understood compared with the intensive studies of the ENSO-related terrestrial carbon dynamics (Bastos et al., 2018; Kim et al., 2017; Liu et al., 2017; Wang et al., 2016; Wang, Zeng, Wang, Jiang, Wang, & Jiang, 2018; Wang, Zeng, Wang, Jiang, Chen, et al., 2018; Zeng et al., 2005). A limited number of studies (Wang et al., 2021; Williams & Hanan, 2011) based on model-simulated and satellite-derived gross primary productivity (GPP) have shown that the IOD could cause large anomalies in land photosynthesis over the IORC. Importantly, although uncertainties exist in future multimodel projections, extreme pIOD events are projected to become more frequent with global warming (Cai et al., 2014, 2020; Wang et al., 2021). Stronger modulations of the IOD on variations in GPP are suggested with increases in the explained variance by up to 10% over central and eastern Africa, Sumatra, and western and southeastern Australia in the future based on future projections of 10 Earth System Models (Wang et al., 2021).

Here, we investigated the impact of the extreme pIOD in 2019 on terrestrial net biome productivity (NBP) and its constituent fluxes over the IORC, based on the posterior fluxes optimized by the Global Carbon Assimilation System Version 2 (GCASv2) (Jiang et al., 2022, 2021), simulations from twelve state-of-the-art Terrestrial Biosphere Models (TBMs) that participated in the TRENDYv9 multimodel intercomparison (Sitch et al., 2015), two satellite-derived global GPP products, and the relevant climate data sets.

2. Materials and Methods

2.1. Global Carbon Assimilation System Version 2 (GCASv2)

GCASv2, an updated version of GCASv1, has the ability to assimilate the satellite-observed XCO₂. Its structure, implementation, and differences from GCASv1 have previously been described in detail (Jiang et al., 2021). GCASv2 adopted the assimilation technique of the ensemble square root filter (EnSRF) algorithm (Whitaker & Hamill, 2002) to assimilate the GOSAT ACOS XCO₂ version 9.0 Level 2 Lite product (O'Dell et al., 2012) within a 1-week window and generated the posterior results (both land and ocean fluxes) at 1° × 1° with prescribed carbon emissions induced by fossil fuel and wildfires from 2010 to 2019 (Jiang et al., 2022). The transport model in GCASv2 is the Model for Ozone and Related chemical Tracers, version 4 (MOZART-4) (Emmons et al., 2010). It was driven by the GEOS-5 meteorological fields with a horizontal resolution of 1.9° × 2.51° and 56 vertical layers. The prior surface carbon fluxes include (a) fossil fuel carbon emissions, which were calculated as the average of the Carbon Dioxide Information Analysis Center product (Andres et al., 2011) and the Open-source Data Inventory of Anthropogenic CO₂ emission product (Oda et al., 2018); (b) ocean carbon fluxes, which were from the pCO₂-Clim prior of CT2019B derived from the climatology of seawater pCO₂ (Takahashi et al., 2009); (c) land carbon fluxes (net ecosystem exchange [NEE]), which were simulated by using the Boreal

Ecosystem Productivity Simulator (Chen et al., 1999), a process-based and remote sensing data-driven ecosystem model; and (d) wildfire carbon emissions, which were from the Global Fire Emissions Database version 4.1 (GFEDv4) (van der Werf et al., 2017). For this study, we performed additional validations at several surface flask sites across the study regions, showing the good performance of GCASv2 (Table S1 and Figure S2 in Supporting Information S1), and made a comparison with the ensemble NBP anomalies from OCO-2 v10 MIP LNLG experiment (Byrne et al., 2022) in September–December (SOND) 2019, showing that except over the Indo-China peninsula, they have basically consistent anomalous NBP patterns and comparable magnitudes over other regions of the IORC (Text S1 and Figure S3 in Supporting Information S1).

2.2. TRENDYv9 Simulations

We analyzed simulations from 12 state-of-the-art TBMs involved in the TRENDYv9 experiment, excluding some models that did not provide the relevant variables and three models (CLM5.0, SDGVM, and VISIT) whose NBP anomalies in SOND 2019 showed the lowest pattern correlation coefficients with the multimodel ensemble result over the IORC. Models in this study include CABLE-POP (Haverd et al., 2018), CLASSIC (Melton et al., 2020), IBIS (Yuan et al., 2014), ISAM (Meiyappan et al., 2015), ISBA-CTRIIP (Delire et al., 2020), LPJ (Poulter et al., 2011), LPX-Bern (Lienert & Joos, 2018), OCN (Zaehle & Friend, 2010), ORCHIDEE (Krinner et al., 2005), ORCHIDEE-CNP (Goll et al., 2017), ORCHIDEEv3 (Vuichard et al., 2019), and YIBs (Yue & Unger, 2015) (Table S2 in Supporting Information S1). More detailed descriptions of these models have been provided in a previous study (Friedlingstein et al., 2020). The same experimental protocol was followed by these models in the TRENDY project, with the S3 run used here. In the S3 run, all the time-varying drivers—including the global atmospheric CO₂, climate, land use, gridded atmospheric N deposition, and N fertilizers—were taken into account to force the models (Sitch et al., 2015). In this study, the relevant variables were consistently interpolated into a horizontal resolution of 1° × 1° by using the first-order conservative remapping scheme (Jones, 1999).

2.3. GOSAT Level 3 XCO₂ Product

The GOSAT Level 3 global CO₂ distribution product version 02.90 (O'Dell et al., 2012) was used in this study to infer the atmospheric XCO₂ anomalies related to the surface anomalous carbon fluxes. The FTS SWIR Level 3 CO₂ product was constructed by interpolating, extrapolating, and smoothing the FTS SWIR Level 2 column-averaged mixing ratios of CO₂ with the kriging method on a monthly basis. This product has a time period starting from June 2009 and a horizontal resolution of 2.5° × 2.5°.

2.4. Satellite-Derived GPP Products

We adopted two satellite-based global terrestrial GPP products to decompose the posterior NBP into its constituent fluxes in the carbon assimilation system: the GOSIF GPP (Li & Xiao, 2019b) and FluxSat GPP (Joiner et al., 2018). We used their average and standard deviation to represent the GPP anomalies and uncertainties induced by the pIOD in 2019 over the India-Africa and Asia-Pacific regions.

The GOSIF GPP product was generated based on the global, fine-resolution Orbiting Carbon Observatory-2 (OCO-2)-based SIF product (GOSIF) (Li & Xiao, 2019a) and linear relationships between solar-induced fluorescence (SIF) and GPP across a wide variety of biomes at both site and grid cell levels. The GOSIF product is provided at 0.05° and each 8 days across the globe from 2000 to 2020. The FluxSat version 1 GPP product was generated by using satellite-based geometry-adjusted reflectances from the MODIS and SIF from the Global Ozone Monitoring Experiment 2 (GOME-2) within a simplified light-use efficiency framework without any meteorological inputs. The monthly FluxSat GPP product used here had a 0.5° spatial resolution since 2000.

2.5. Climate Data Sets

Land precipitation and surface air temperature were obtained from the version 4.05 of the Climatic Research Unit (CRU) Time Series (TS) monthly high-resolution gridded data set at 0.5° spatial resolution (Harris et al., 2020). The root zone soil moisture was from the NASA's Global Land Data Assimilation System (GLDAS) Noah land Surface Model L4 monthly V2.1 data set (GLDAS_NOAH025_M) at 0.25° spatial resolution (Rodell et al., 2004). And the root depth in Noah depends on the vegetation types. The SST and U and V winds at 50 and 200 hPa were

adopted from the ERA5 reanalysis data set (Hersbach et al., 2020). The ERA5 data set was produced by using 4D-Var data assimilation and model forecasts in CY41R2 of the ECMWF Integrated Forecast System, with 137 hybrid sigma/pressure levels in the vertical and 31 km horizontal resolution.

2.6. Velocity Potential and Divergent Winds

To investigate the climate extremes-related atmospheric circulation adjustments caused by the extreme pIOD in 2019, we here adopted the concepts of velocity potential and divergent winds at 200 hPa to illustrate the atmospheric vertical motion and divergence, following the previous analysis (Wang et al., 2021). According to the Helmholtz theorem, the horizontal velocity vector (\vec{v}) can be decomposed into irrotational (\vec{v}_χ , divergent winds) and nondivergent (\vec{v}_ψ) parts:

$$\vec{v} = \vec{v}_\chi + \vec{v}_\psi = \nabla_H \chi + \vec{k} \times \nabla_H \psi, \quad (1)$$

where χ is the velocity potential, ψ is the stream function, and ∇_H is the horizontal vector differential operator. The \vec{k} represents the unit vector directed vertically. Taking the divergence of Equation 1, we can obtain the following equation:

$$\nabla^2 \chi = \nabla \cdot \vec{v} = \text{Div}, \quad (2)$$

where Div is the horizontal divergence. Solving this Poisson's equation, we can derive the velocity potential and then the divergent winds.

2.7. Anomaly Calculation

As a result of the short-term period (10 years) of the posterior results from GCASv2, we derived the anomalies of all the carbon fluxes by removing their climatology calculated from 2010 to 2019. For the GOSAT L3 XCO₂ product, we first detrended the monthly XCO₂ at each grid, which is largely caused by anthropogenic fossil fuel emissions, simply by removing the corresponding zonal average. We then calculated the XCO₂ anomalies used in this study by removing their climatology calculated from 2010 to 2019.

3. Results and Discussion

3.1. Pattern of NBP Anomalies Induced by the 2019 Extreme pIOD Associated With Its Climate Drivers

The posterior NBP anomalies averaged from SON 2019 in GCASv2 showed contrasting behaviors over the IORC, exhibiting enhanced carbon uptake (positive values) over western, eastern, and central Africa and India, but enhanced carbon release (negative values) over southern Africa, East Asia, the Indo-China peninsula, Indonesia, and Australia (Figure 1a). TRENDYv9 multimodel ensemble NBP anomalies suggested a similar spatial pattern, although the magnitudes differed in some regions (Figures 1a and 1b). For instance, the enhanced carbon uptake indicated by the TRENDYv9 ensemble NBP was weaker than the GCASv2 NBP over eastern Africa but was stronger over India (Figures 1a and 1b). However, patterns of NBP anomalies in TBMs showed a large inter-model spread (Figure S4 in Supporting Information S1) despite following the same experimental protocol, likely caused by differences in model structures and parameters (Rogers et al., 2014; Sitch et al., 2015).

From the perspective of atmospheric CO₂ concentration, persistent anomalies in surface carbon sources and sinks can result in regional atmospheric CO₂ concentration anomalies. Satellite-observed XCO₂ concentrations can directly detect anomalies in terrestrial carbon fluxes in local or upwind regions to some extent (Figure 1c), despite the interference from atmospheric advection and divergence. Obvious reductions in the GOSAT L3 XCO₂ anomalies occurred over the vast areas to the north of Lake Victoria in Africa (Figure 1c), which corresponded well with enhanced terrestrial carbon uptake in this region associated with the prevailing southeasterly winds in the lower troposphere (Figure 1a). By contrast, there were clear increases in the XCO₂ anomalies over East Asia, the

Anomalies in September to December 2019

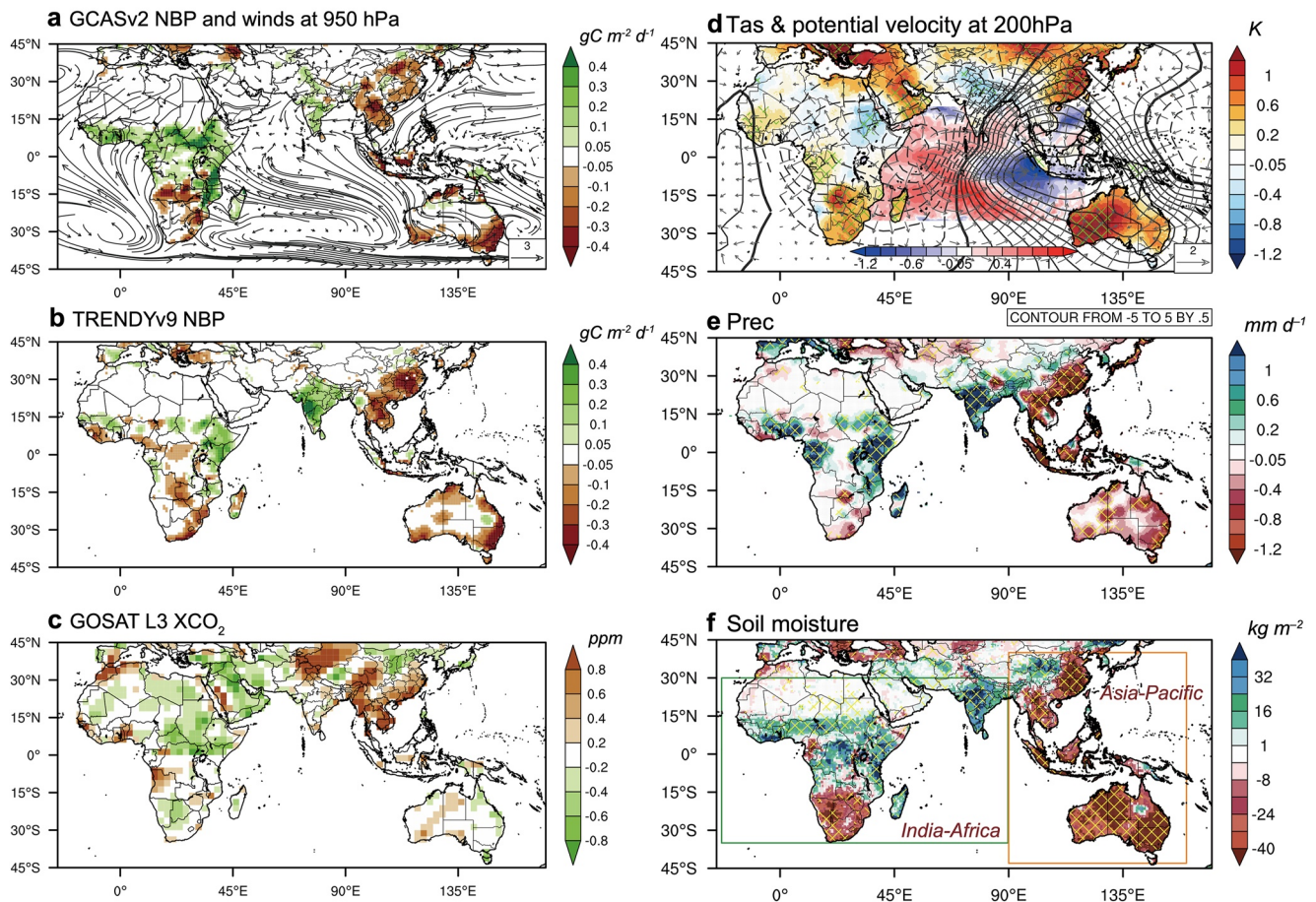


Figure 1. Patterns of terrestrial carbon flux, atmospheric XCO₂, and climate anomalies averaged from September to December (SOND) 2019. (a) Posterior net biome productivity (NBP; positive indicates a flux from the atmosphere to the land) optimized by the Global Carbon Assimilation System Version 2.0 (GCASv2) and winds at 950 hPa (arrows). (b) Ensemble NBP anomalies simulated with multiple models involved in TRENDYv9. The units of NBP and winds in (a) and (b) are $\text{gC m}^{-2} \text{d}^{-1}$ and m s^{-1} , respectively. (c) GOSAT L3 XCO₂ anomalies over lands in ppm. (d) Surface air temperature anomalies and sea surface temperature over the tropical Indian Ocean (k) associated with the anomalies of velocity potential (contours) and divergent winds at 200 hPa (arrows) with respective units of $10^6 \text{ m}^2 \text{ s}^{-1}$ and m s^{-1} . (e) Precipitation anomalies (mm d^{-1}). (f) Global Land Data Assimilation System root zone soil moisture anomalies (kg m^{-2}). The green and orange boxes in (f) represent the two land regions of India-Africa and Asia-Pacific used to calculate the total terrestrial carbon fluxes and anomalies. The cross-hatched areas represent variations in SOND stronger than $\pm 1-\sigma$ during the time period of 2010–2019.

Indo-China peninsula, Sumatra, Kalimantan Island, and western parts of Australia (Figure 1c), and the increases in XCO₂ anomalies in these regions were consistent with the enhancement of carbon release (Figure 1a).

These NBP anomalies over the IORC can be largely accounted for by the anomalous weather and climate induced by the extreme pIOD in 2019. The warm pole of the extreme pIOD over the equatorial western Indian Ocean favored active convection (Figure 1d), resulting in high precipitation over western, eastern, and central Africa and India (Figure 1e). More precipitation led to a wetter land surface (Figure 1f), more evapotranspiration, and thus more evaporative cooling and lower near-surface air temperature (Figure 1d) as a result of the control of thermodynamics and the hydrological cycle on the surface energy balance over the tropics (Zeng & Neelin, 1999). The cool and wet conditions enhanced terrestrial carbon uptake over these regions (Figures 1a and 1b) likely due to strengthened terrestrial photosynthesis (Wang et al., 2021; Zeng et al., 2005; Zscheischler et al., 2014), reduced soil respiration, and inhibition of wildfires (Kim et al., 2019). By contrast, atmospheric subsidence prevailed over East Asia, the Indo-China peninsula, Indonesia, and Australia due to the cold pole of the pIOD over the southeastern equatorial Indian Ocean (Figure 1d). This caused a reduction in precipitation (Figure 1e), higher temperatures (Figure 1d), and thus widespread heatwaves and droughts (Figures 1d and 1f). These climate extremes, a multivariate compound event, can potentially reduce photosynthesis by stomatal and xylem

regulation (Bastos et al., 2021; Konings et al., 2017; Peters et al., 2018; Wang et al., 2021), increase vegetation mortality (Senf et al., 2020; Stovall et al., 2019), increase soil respiration (Anjileli et al., 2021), and promote wildfires (Boer et al., 2020; Wang et al., 2020), hence enhancing anomalous carbon release there (Figures 1a and 1b).

In the developing phase of the pIOD during June–August (JJA) 2019 (Figure S5c in Supporting Information S1), the enhanced convection and subsidence associated with the pIOD were weaker than those during SON 2019 (pIOD peaked in October) (Figure 1d). Nevertheless, it had already to some extent enhanced precipitation over Africa north of the Equator and India, and reduced precipitation over southern China, the Indo-China peninsula, Sumatra, Kalimantan Island, and southeastern Australia (Figure S5d in Supporting Information S1). Compared to the precipitation pattern in March–May (MAM) 2019, which was largely influenced by the weak El Niño event in 2018 (Figure S5b in Supporting Information S1), these changes in precipitation in JJA 2019 indicate the gradual transition from the control of El Niño to the control of pIOD, which also manifested in changes of NBP. Increased carbon uptake over the Africa north of the Equator and western coast of India could be found in both of the GCASv2 and TRENDYv9 ensemble result (Figures S6c and S6d in Supporting Information S1). An obvious carbon release was found over southern China in JJA (Figures S6c and S6d in Supporting Information S1) which was associated with decreased precipitation (Figure S5d in Supporting Information S1), differing from the weak uptake there in MAM (Figure S6b in Supporting Information S1) caused by the El Niño-induced more precipitation (Figure S5b in Supporting Information S1). Additionally, there was an obvious reduction in carbon release over Australia from MAM to JJA (Figure S6 in Supporting Information S1). These changes in NBP anomalies from MAM to JJA make us more confident that NBP anomalies in SON 2019 focused in this study were mainly induced by the extreme pIOD event (Figures 1a and 1b).

3.2. Seasonal Variations of Total Regional NBP Anomalies

Given that the 2019 extreme pIOD had differential impacts on the terrestrial carbon sources and sinks over the IORC (Figures 1a and 1b), we simply separated these regions into two parts: the India-Africa and Asia-Pacific regions (Figure 1f).

Over the India-Africa region, the seasonal variation in GCASv2 NBP showed net carbon uptake from August to October and net carbon release in other months (Figure 2a). In 2019, the anomalous carbon release relative to the average from 2010 to 2019 occurred before August, followed by the anomalous carbon uptake, with the averaged anomalies of -0.06 ± 0.15 PgC in JJA and 0.23 ± 0.20 PgC in SON (Figure 2a). The TRENDYv9 ensemble showed carbon uptake from June to October and carbon release in other months (Figure 2c), which was somewhat different from the GCASv2 (Figure 2a). The anomalies in 2019 (0.02 ± 0.07 PgC in JJA and 0.11 ± 0.15 PgC in SON) based on TRENDYv9 were slightly weaker than those in GCASv2 (Figures 2a and 2c). These positive anomalies in the total NBP in SON were linked to the enhanced carbon uptake over western, eastern, and central Africa and India (Figures 1a and 1c). The 2015 extreme El Niño caused anomalous carbon release in the tropics with no obvious lagged response (Bastos et al., 2018; Liu et al., 2017; Wang, Zeng, Wang, Jiang, Wang, & Jiang, 2018). By comparison, in 2015, GCASv2 showed nearly neutral anomalies (-0.01 ± 0.15 PgC) in JJA and obvious carbon release (-0.28 ± 0.19 PgC) in SON (Figure 2a), and the TRENDYv9 ensemble indicated carbon release of -0.11 ± 0.09 PgC in JJA and -0.14 ± 0.11 PgC in SON (Figure 2c). Both products showed the comparable magnitudes but different signs of carbon anomalies in SON induced by the 2019 extreme pIOD and 2015 extreme El Niño events (Figures 2a and 2c), which can be clearly seen from their different spatial patterns of NBP and climate anomalies in these two events (Figure 1 and Figures S7 and S8 in Supporting Information S1). It suggests that, in addition to ENSO events, IOD events can also play an important part in influencing regional carbon cycling.

Over the Asia-Pacific region, GCASv2 and TRENDYv9 showed similar seasonal variations in NBP and both showed net carbon uptake from April to October, although the magnitudes differed (Figures 2b and 2d). Carbon anomalies in 2019 showed enhanced carbon release in all months, which was consecutively influenced by the lagged effects (Wang et al., 2016) of the weak El Niño in 2018 and the extreme pIOD in 2019 (Figures S1 and S6 in Supporting Information S1). The anomalous carbon release was -0.18 ± 0.12 PgC in JJA and -0.38 ± 0.15 PgC in SON in GCASv2, and -0.08 ± 0.08 PgC in JJA and -0.23 ± 0.20 PgC in SON in the TRENDYv9 ensemble, respectively (Figures 2b and 2d). By comparison, the 2015 extreme El Niño event also caused anomalous carbon release in SON (somewhat weaker than those in 2019), with anomalies of -0.28 ± 0.16 PgC in GCASv2 and -0.18 ± 0.12 PgC in the TRENDYv9 ensemble, respectively (Figures 2b and 2d).

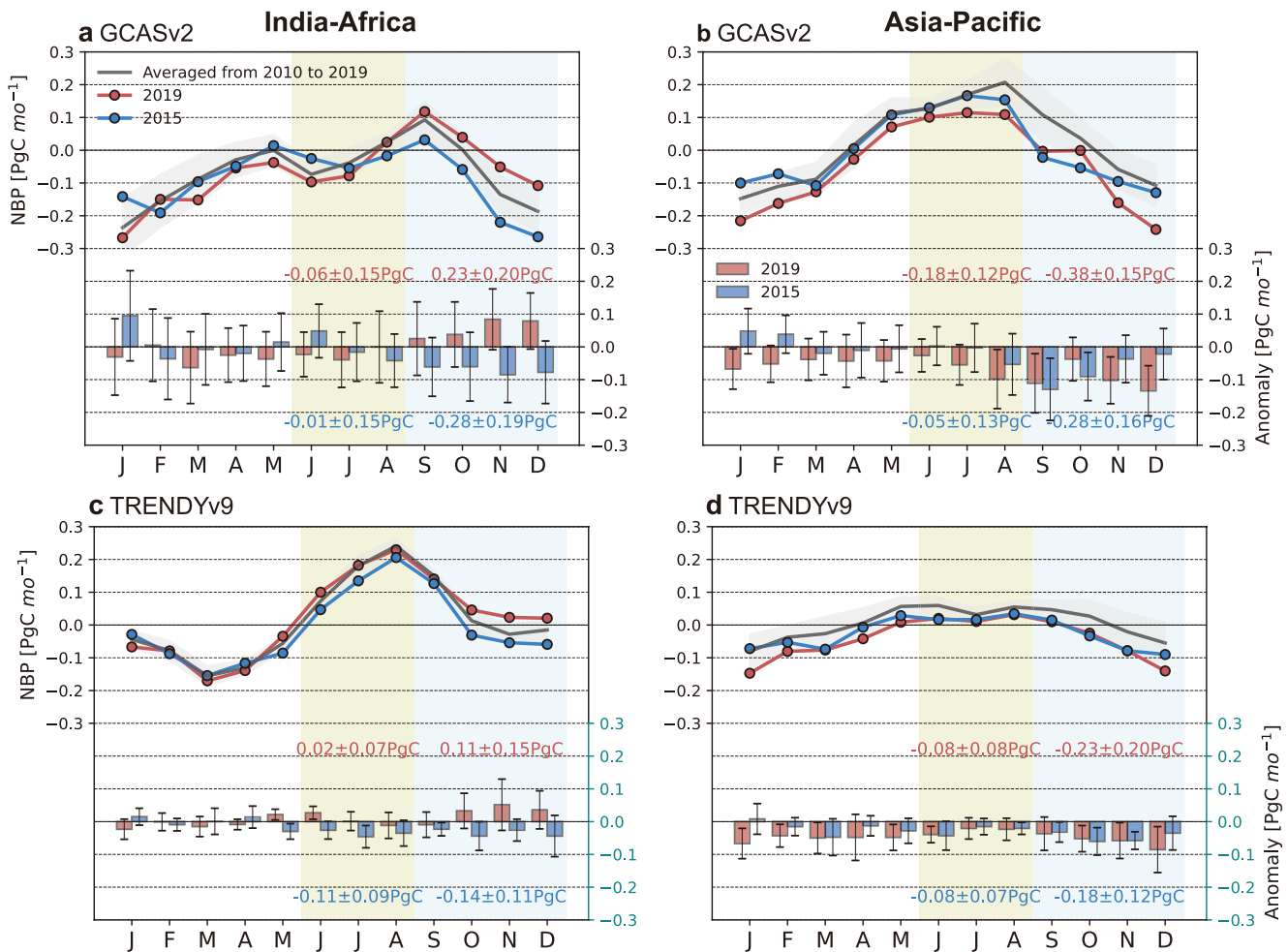


Figure 2. Seasonal variations in total net biome productivity (NBP) and its anomalies over the India-Africa and Asia-Pacific regions. The posterior total NBP anomalies in 2015 and 2019 optimized by Global Carbon Assimilation System for the (a) India-Africa and (b) Asia-Pacific regions. The error bars in (a and b) are the uncertainties calculated from the optimization process. The TRENDYv9 ensemble NBP in 2015 and 2019 for the (c) India-Africa and (d) Asia-Pacific regions. The error bars in (c and d) represent the standard deviation among different models. The light gray shaded areas represent the standard deviation of the NBP for each month from 2010 to 2019. The light orange and blue shaded areas in the subplots represent June–August and September–December.

In addition, the historical variations in the NBP during SON, in general, had stronger partial correlation coefficients (*pcor*) with the root zone soil moisture (controlling the effect of temperature) than with temperature (controlling the effect of soil moisture) for both the India-Africa and Asia-Pacific regions, except that the TRENDYv9 ensemble had equivalent *pcor* with the root zone soil moisture and temperature over the India-Africa region (Table S3 in Supporting Information S1). This indicates that soil moisture played a more important role in these regional NBP variations, in agreement with the findings of previous studies (Humphrey et al., 2018; Humphrey et al., 2021; Wang, Zeng, Wang, Jiang, Chen, et al., 2018; Zscheischler et al., 2014), as would also be expected in tropical regions.

3.3. Biological Mechanisms

The carbon balance over land is represented by $NBP = NEP - D = GPP - TER - D$, where NEP denotes net ecosystem productivity, D is the carbon release induced by both natural and anthropogenic disturbances such as wildfires, harvests, grazing, and land cover change, and TER is the total ecosystem respiration. We decomposed NBP anomalies during SON in 2019 into its different constituent fluxes. In GCASv2, we optimized the terrestrial NEE or $-NEP$ and ocean carbon flux using satellite CO_2 column data, while D mainly represents the prescribed carbon emission induced by wildfires. In this study, we used the average of GOSIF GPP (Li &

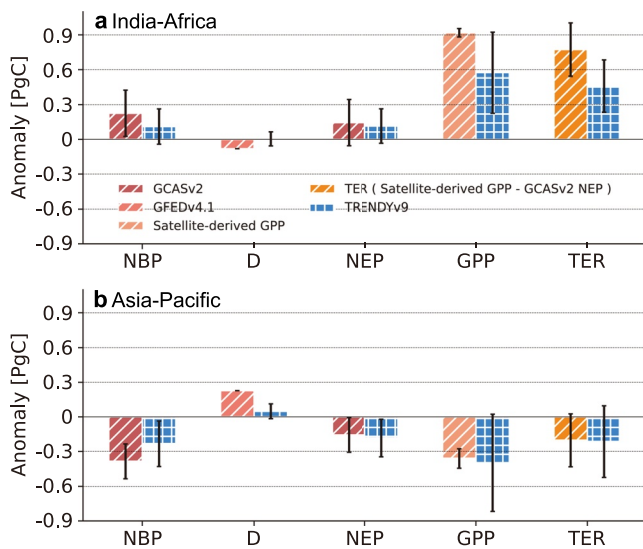


Figure 3. Anomalies in the net biome productivity (NBP) and its constituent fluxes during September–December 2019. (a) Terrestrial carbon fluxes over the India-Africa region. (b) Terrestrial carbon fluxes over the Asia-Pacific region. The constituent fluxes of the NBP in the TRENDYv9 ensemble were simulated with the intermodel spread (standard deviation among different models; error bars). The term *D* is the residual between simulated net ecosystem productivity (NEP) and NBP, which includes fluxes of simulated wildfires, grazing, harvest etc. In GCASv2, the uncertainties in the NBP and NEP (error bars) are calculated from the optimization process. *D* is only composed of the fluxes of wildfires based on the Global Fire Emissions Database without uncertainties, we supposed. The gross primary productivity (GPP) is the average of the GOSIF GPP and FluxSat GPP with their standard deviation as uncertainties. The total ecosystem respiration is calculated as the difference between the satellite-derived GPP and the GCASv2 optimized NEP.

Xiao, 2019b) and FluxSat GPP (Joiner et al., 2018), two satellite-based GPP products, to calculate the GPP anomalies. TER is therefore derived as the difference between the satellite-derived GPP and optimized NEP.

Over the India-Africa region (Figure 3a), the enhanced NEP (0.14 ± 0.20 PgC) accounted for 60.87% of the enhanced NBP (0.23 ± 0.20 PgC) in GCASv2 induced by the wet and cool conditions during SOND (Figures 1d–1f). The increase in the NEP resulted from the stronger enhancement in the GPP (0.92 ± 0.04 PgC) than in the TER (0.77 ± 0.23 PgC). In the TRENDYv9 ensemble results, the enhanced NEP (0.12 ± 0.15 PgC) accounted for 103.97% of the variation in the NBP, with the enhancement in the NEP similarly caused by the stronger enhancement in the GPP (0.57 ± 0.35 PgC) than in the TER (0.46 ± 0.22 PgC).

Over the Asia-Pacific region (Figure 3b), the anomalies in the *D* and NEP accounted for 59.17% and 40.83% of the reduced NBP (-0.38 ± 0.15 PgC) in GCASv2 caused by the dry and heat compounds (Figures 1d–1f), respectively. A stronger reduction in the GPP (-0.36 ± 0.08 PgC) than in the TER (-0.20 ± 0.23 PgC) appeared to cause the reduction in the NEP. The reduction in the NEP estimated by the TRENDYv9 ensemble (-0.18 ± 0.16 PgC) was comparable with the magnitude in GCASv2, but the reduction in the NEP accounted for a much larger fraction of the variation of the NBP in the TRENDYv9 ensemble (79.18%) than in GCASv2. The anomalies in the GPP (-0.40 ± 0.42 PgC) and TER (-0.21 ± 0.31 PgC) in the TRENDYv9 ensemble had comparable magnitudes to the estimates in the satellite-derived GPP and calculated TER.

Quantitatively, the GPP had the largest variations among these three processes (GPP, TER, and *D*) over both of India-Africa and Asia-Pacific regions and dominated the enhanced terrestrial carbon uptake and release over the India-Africa and Asia-Pacific regions, respectively (Figure 3). The reductions in the GPP and TER simulated in the TRENDYv9 ensemble had large intermodel spreads due to their different model structures and parameters; their individual estimates are illustrated in Tables S4 and S5 in Supporting Information S1. Furthermore, the carbon flux anomaly mainly induced by wildfires (*D*) was substantially underestimated in the TRENDYv9 ensemble results (Figure 3). We found that this substantial underestimation in *D* anomalies still existed although we derived the magnitude by only using the models that explicitly included the fire modules (Tables S2, S4, and S5 in Supporting Information S1). This indicated that the underestimation in *D* anomalies was largely caused by the absence and underrepresentation of wildfire in the models (Table S2 in Supporting Information S1). If the magnitudes of the wildfire-induced carbon anomalies simulated by the TRENDYv9 ensemble were close to the magnitudes derived from satellites (van der Werf et al., 2017), as used in GCASv2, then the magnitudes of the total NBP anomalies over the two regions would have been comparable between GCASv2 and the TRENDYv9 ensemble (Figure 3).

4. Conclusions

We in this study comprehensively investigated the impact of the 2019 extreme pIOD on terrestrial NBP and its constituent fluxes, and quantitatively compared it with the impact of the 2015 extreme El Niño during SOND. GCASv2 posterior NBP and TRENDYv9 multimodel ensemble NBP anomalies basically showed similar pIOD-induced spatial patterns, exhibiting enhanced carbon uptake over western, eastern, and central Africa and India, but enhanced carbon release over southern Africa, East Asia, the Indo-China peninsula, Indonesia, and Australia. It caused an enhanced total terrestrial carbon uptake of 0.23 ± 0.20 PgC in GCASv2 and 0.11 ± 0.15 PgC in TRENDYv9 ensemble over the India-Africa region, and the enhanced total release of 0.38 ± 0.15 PgC in GCASv2 and 0.23 ± 0.20 PgC in TRENDYv9 ensemble over the Asia-Pacific region, respectively. We further revealed that these regional NBP anomalies were more closely related to soil water availability with a dominant role of GPP. Importantly, these two data sets showed comparable magnitudes to those following

the 2015 extreme El Niño event although this event led to the consistent release of carbon in both India-Africa and Asia-Pacific regions. This suggests that, other than ENSO events, IOD events can also drive variations in the regional terrestrial carbon cycling. Along with more frequent extreme pIOD events in future greenhouse warming, it may also modulate the long-term land carbon accumulations (Cai et al., 2014; Park et al., 2020).

Data Availability Statement

Land precipitation and surface air temperature from CRU TS v. 4.05 are available at <https://crudata.uea.ac.uk/cru/data/hrg/>. GLDAS-2.1 soil moisture is maintained at the NASA Goddard Earth Science Data and Information Services Center (GES DISC) with the web site at <https://disc.gsfc.nasa.gov/datasets>. Winds at 950 and 200 hPa from ERA5 are available at <https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-pressure-levels-monthly-means?tab=form>. GOSIF GPP and FluxSat GPP products are provided at <https://globalecology.unh.edu/data/GOSIF-GPP.html> and https://avdc.gsfc.nasa.gov/pub/tmp/FluxSat_GPP/, respectively. The TRENDY DGVMs data are available at <https://sites.exeter.ac.uk/trendy>. GCASv2 output are available at <https://zenodo.org/record/5829774>.

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