Environmental Control of Inter-annual Variability of Net Ecosystem Exchange in Rice-rice Cropping System

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Abstract

Consecutive five-year long eddy covariance measurements in a lowland tropical rice-rice system were used to investigate the impacts of gross primary productivity (GPP), climate drivers and ecosystem responses (i.e. ecosystem respiration, RE) on the inter-annual variability (IAV) of the net ecosystem exchange (NEE), which is directly related to the agricultural productivity and climate change. The IAV of carbon dioxide fluxes in two crop growing phases i.e. dry and wet season along with fallow period were analysed. The respiratory fluxes build up during the non-growing season were lower by net uptake in growing season. Annual cumulative value of NEE was negative (sink) in both the crop growing season. The variability of climate drivers and changes in the ecosystem responses to drivers revealed a large intra-annual as well as inter-annual variability of net ecosystem fluxes. NEE was found to be strongly correlated with GPP and RE and also with other metrological variables such as photosynthetically active radiation (PAR), precipitation, air temperature and soil temperature. The anomalies of NEE, GPP and RE were observed to be less in 2017 and 2018 which may be due to lower temperature anomalies recorded in these years. Further understanding of biological mechanisms is needed which is involved in the variation of climatological variables to improve our ability to predict future IAV of NEE.

1. Introduction

Large emission of anthropogenic carbon dioxide (CO_2) into the atmosphere imposes threat to human civilization by inducing climate change (Solomon et al. 2009). The global CO_2concentration is exponentially increasing day by day (2.04 ppmv at present compared to 0.84 ppmv during 1960s) and its deleterious impact on the ecosystem as well as the future climate change is well predicted (Chatterjee and Saha, 2018). Agriculture contributes 16% of total greenhouse gas (GHG) emissions in India (MoEFCC, 2018) including contribution from flooded rice in India. Quantification of anthropogenic CO_2 emission in any ecosystem can be useful for exploring climate change mitigations options (Le Quere et al. 2018). Some studies in India have reported lowland rice behaved as net carbon sink (Bhattacharyya et al. 2014; Swain et al. 2016).

About 90% of the global rice production is mostly contributed by the Asian countries such as India, China, the Philippines, Japan, and Bangladesh (Masseroni et al. 2015). Rice ecosystem has been reported to have varying carbon source and sink capacity depending on the various cultivation practices and irrigations regimes. In India, rice-rice cropping system is one of the dominant production system of cultivation mostly found in the coastal regions and is reported as net carbon sink (Bhattacharyya et al. 2016; Swain et al. 2016). Need for understanding this variability is long standing as the source sink status of the production system is required to assess the effect of NEE on climate change and subsequently the impact of climate on the terrestrial carbon cycle. Photosynthetic active radiation (PAR), soil temperature, precipitation, and air temperature are the major drivers controlling net ecosystem exchange (NEE), gross primary productivity (GPP), and ecosystem respiration (RE) (Swain et al. 2016; Swain et al. 2018). The RE and GPP have been mentioned to be tightly connected in several ecosystems on both short-term and annual timescales (Ryan and Law, 2005) and respond similarly, although now not

always with the same magnitude. Therefore, to interpret the inter-annual variability (IAV) in NEE, it is crucial to partition NEE into GPP and RE and investigate their dynamics with respect to meso-meteorological parameters. Improved representation of long time series data of lowland tropical rice-rice ecosystem in various climatic conditions, improve the understanding of the causes and effect associated with carbon exchange variability. The knowledge of correlations of NEE with various weather variables is required to understand the variation of NEE throughout crop growing season.

However, in order to have a better insight on the IAV of carbon sequestration by ecosystems, long term carbon exchange studies are needed. Since the end of the nineteenth century, several networks have been established around the globe to record CO_2 fluxes, viz. Euroflux (Valentini et al. 2000), Fluxnet (Baldocchi et al. 2001), Asiaflux (Yamamoto and Kagi, 2006), CarboEurope (Schulze at el., 2010), Ameriflux (Novick et al. 2018), Ozflux (Gorsel et al. 2018), ICOS (Rebmann et al. 2018) using the eddy covariance method (Aubinet et al. 2012). Globally, the main concern of the scientific community is to understand the processes associated with the carbon cycle and the role of meteorological drivers, such as temperature, precipitation and radiation in carbon budget (Smith et al. 2010). In addition to this, the IAV of these environmental variables is a key to understand the inter-annual variability of CO_2 fluxes especially for agricultural crops. The present understanding of IAV is scarce due to the lack of long-term observation system (Richardson and Hollinger, 2007; Bhattacharyya et al. 2016). In the present study we have analysed five year-long (2014–2018) continuous eddy covariance flux data recorded in a rice paddy ecosystem with the following objectives: (1) to characterize the weekly, seasonal and inter-annual variations of NEE (2) to identify the associated meteorological drivers of carbon fluxes and the time lags between climate and ecosystem responses (3) to study the inter-annual variations of carbon fluxes and changes in ecosystem responses due to meteorological factors.

2. Material And Methods

2.1. Observation site and experimental set-up

The study was conducted in the research farm of ICAR-National Rice Research Institute, Cuttack, Odisha, India, situated at a latitude of 20° 27´ 6´´ N, and longitude of 85° 56´ 25´´ E and at an altitude of 24 m above mean sea level from 2014-2018 under rice-rice cropping sequence. The mean annual rainfall and temperature were 1250-1450 mm and 27.9°C, respectively while the highest and lowest mean annual temperatures were 38.3 and 23.4°C, respectively. The soil of the site is an Aeric Endoaquept with sandy clay loam texture, bulk density 1.38 Mg m^{-3}, pH (1:2.5 soil:solution ratio) 6.20, electrical conductivity 0.41 dS m^{-1}, total C 11.1 g kg^{-1} and total N 0.78 g kg^{-1}. The cropping sequence involve two fallow periods viz. pre-season fallow (mid-May to mid-July) and post-season fallow (third week of November to December). During dry season (DS) (first fortnight of January to first fortnight of May) and wet season (WS) (first fortnight of July to second fortnight of November) the rice seedlings of 25 days old (cv. Naveen (DS) and Pooja (WS)) were planted with a spacing of 20 ×15 cm. The equal rate of recommended dose of Nitrogen (N) (80 kg N ha^{-1} in WS and 100 kg N ha^{-1} in DS) is applied at just before planting, maximum tillering

(MT) and panicle initiation (PI) stages through urea, while the recommended dose of phosphorus (P) and potassium (K) (40 kg ha^{-1}) were applied through single super phosphate and muriate of potash as a basal dose at the time of land preparation in both seasons. Compost containing 245 g C kg^{-1}, 11.5 g N kg^{-1}, 3.9 g P $kg^{-1}$and 6.1 g K kg^{-1} was applied only in WS at the rate of 5 Mg ha^{-1} before primary tillage with mouldboard plough and secondary tillage with cultivator. During the cropping period the research field was kept flooded with 6±2 cm standing water and drained out 15±2 days before harvest.

In eddy covariance based study, net ecosystem exchange of CO_2 refers to the net CO_2 flux or balance of all CO_2 entering an environment and the measure of CO_2 leaving the biological system during a particular time of intrigue (Chapin et al. 2006). RE is total of the metabolic respiration from both above and subterranean biomass just as the heterotrophic respiration coming about because of microbial degradation of organic matter in the soil. In this study site, eddy covariance system used for observing real time continuous data of NEE, air temperature (AT), soil temperature (ST), PAR mounted at a height of 1.5m on a tripod aluminium pole in the middle of the agriculture field with around 2.0 ha fetch area of the study site whereas daily precipitation data is collected separately from Agromet observatory of ICAR-NRRI. The fluctuations in CO_2 and water vapour densities in high speed (10 Hz) real time basis, an open path infrared gas analyser (LI-7500A, M/s LICOR Inc., USA) used to measure. The NEE was considered to sum-up the eddy CO_2 flux (Fc) and CO_2 storage changes (Fs) whereas Fs was ignored because of the canopy height which was moderately low at the observation site.

2.2. Flux calculation

The data were processed using EdiRe programming software (University of Edinburgh). However, in term of processing the fluxes it applied cross products necessary for off-line coordinate rotation (Tanner and Thurtell, 1969; Webb et al. 1980; Kaimal and Finnigan, 1994). The EC flux dataset was checked for the quality as given by Mauder and Foken (2011). The flux data were corrected considering time delays of different sensors and physically unacceptable values were discarded (Vickers and Mahrt, 1997). High spikes in data due to unsuitable natural conditions were removed utilizing U* separating (Reichstein et al. 2005; Papale et al. 2006; Bhattacharyya et al. 2014). The gap-filling of lost and unwanted data was done by “look-up” table methodology (Falge et al. 2001). The half-hourly averaged NEE was partitioned into RE and GPP (Kolari et al. 2008) as described using half-hourly averaged incident PAR estimated over the overhang with quantum sensor (LI-7500A, M/s LICOR Inc., USA) and EC measurements. In this partitioning method, RE was calculated using Rectangular hyperbola (Ruimy et al. 1995; Kolari et al. 2008), the method used for partitioning of NEE into GPP and RE:

$NEE_{night+day} = - [(\alpha.\beta.Q / \alpha. Q + \beta)] + \gamma$ ---------- Equation (1)

Where, α and β observable quantum yield and hypothetical maximum GPP respectively, “γ” estimate ecosystem respiration, and “Q” photosynthetically active radiation. GPP was determined by utilizing the equation GPP = −NEE + RE, where negative NEE symbolises an uptake of CO_2 by the ecosystem. For both weather and fluxes, multiple “yearly” statistics (i.e. total of five years’ data) were achieved by using a

moving time window of twelve months. The NEE is utilized to indicate the net increase or loss of carbon of an environment and it is controlled by removing the loss of carbon via autotrophic (Ra) and heterotrophic (Rh) respiration from GPP of autotrophic organisms.

NEE = GPP − RE ----------Equation (2)

2.3. Weather variables and net ecosystem carbon exchange fluxes

The relationships between weather variables (such as PAR, ST, AT and precipitation) and also the components of the ecosystem carbon fluxes were centred on the event of time lags between weather drivers and ecosystem responses. Photosynthetically active radiation sensor (PAR) was used to capture the direct radiation on rice canopy. Simultaneously, annual average air, soil temperature probe (5 cm depth) (107 B, Campbell Scientific Corp.) and precipitation were calculated.

2.4. Principal component analysis (PCA)

PCA was carried out to categorise linearly related variables such as NEE, GPP, RE, PAR, AT, ST and precipitation that furthermost of the variability and identification of the most weighed variable among them. ‘R’ software was used for the statistical analysis (Oksanen et al. 2015) while based on Jaccard distance matrices raised using ggplot 2 package principal coordinates analysis were generated (Allaire, 2015). Pearson's correlation is a combination which creates confidence intervals and accomplishes hypothesis test.

2.5. Autocorrelation and lagged auto correlation

Autocorrelation and lagged auto correlation was done using SAS 9.3 (Keele and Kelly, 2006) software. For this analysis, weekly data of climatic variable such as NEE, GPP, RE, PAR, AT, ST and precipitation were used for autocorrelation and lagged correlation with weekly data of NEE. In time series analysis, examining lags and autocorrelation are valuable in getting seasonality and structure the reason for autoregressive predictable models, for example, ARIMA. JMP software (Amin et al. 2014) has been used to calculate the power of a test after it is performed (retrospective power analysis).

Autocorrelation signifies the degree of closeness among a given time series and a lagged version of itself over continuous time intervals. When computing autocorrelation, the output may range from +1 to -1. An autocorrelation of +1 speaks to an ideal positive relationship though - 1 speaks to an ideal negative correlation (an increase found in one-time series results in a proportionate decrease in the other time series). Lag refers to a particular time within a time series to be correlated with previous copies of itself in time series analysis and is considered to be very useful.

2.6. Statistical analysis

Principal component analysis was through using R studio software (Version 1.0.153; 2009–2017 R Studio, Inc., R Studio Team, 2015). In our study, the package ‘factoextra’ were used while ggplot2 plotting

system was used for information visualization (Husson et al. 2007; Le et al. 2008).

3. Result

3.1. Temporal variation of CO_2 fluxes and meteorological variables

The temporal variability of the key climatic drivers is carefully scrutinized to find out its role in ecosystem CO_2 exchange at the study site. For this purpose, the complete data set from 2014 to 2018 were plotted in Fig. 1. The monthly average values of air temperature (standard deviation) and soil temperature from 2014-2018 are depicted in Fig. 1a which were found to vary from 20.42 to 31.53 ºC and 21.62 to 31.94 ºC, respectively. Variability in soil and air temperatures was observed in the year 2014 and 2017, respectively. Soil temperature was found to be significantly and positively correlated with air temperature throughout the study period. A steady increase in the air temperature and soil temperature was observed from dry period to post dry fallow period. After that, both the temperatures dropped and attained the minimum value during winter fallow period. The highest monthly average air temperature was observed in the month of June in 2017.

The PAR was observed to be higher from mid to end of the dry season (mainly crop growing period) than in the wet season. It followed the obvious seasonal pattern being higher during dry fallow compared to the lower in wet fallow period (Fig. 1b). Annual average PAR was found higher in 2015 (20.47%) compared to the rest of the study period. The observation years (2014–2018) were also characterised by higher variability in monthly precipitation (Fig. 1b). In the whole study period, the monthly average precipitation varied from 30.7 mm during 2015 to 213.7 mm during 2016.

Usually, positive anomalies in air temperature were recorded during January to February months as well as during November to December during the study period. Negative anomalies were reported mostly in March to October months (-0.13 to -5.34 ^{o}C). Highest positive anomaly was reported in January (8.25^{o}C) during 2018, while highest negative anomaly in June (-5.34 ^{o}C) during 2017. Positive anomalies of precipitation were recorded during July-August till January throughout the study period. Negative anomalies were reported in March to August 2017 in all the five years. Highest positive anomaly was reported in December (2.33mm), while highest negative anomaly was reported in May, 2016 (-2.87mm). Average year, 2018 showed the highest temperature and precipitation anomalies (Fig. 1c).

The average half hourly NEE showed a wide variability during 2014-2016, while narrow during 2017 and 2018 (Fig. 1d). Half hourly average value of NEE was found to be negative during most of the months coinciding with cropping period throughout the study period while positive values was found in the month coinciding with fallow period. The monthly pattern of net ecosystem exchange (Fig. 1e) was characterised by a large variation in GPP and RE during 2014 to 2016 showing distinct asymmetric bell shaped curve whereas during 2017 and 2018 the variation was almost squeezed. The GPP sharply

increased during growing period with corresponding increase in RE during the study period which was prominent during 2014 to 2016.

A large intra-annual as well as inter-annual variability of ecosystem fluxes were observed between 2014 and 2018 (Fig. 2a). In order to explore the relative significance of various crop growing stages in determining the difference of NEE, annual trend of cumulative weekly NEE averaged over the observation period and its standard deviation was premeditated in Fig. 2b. The variation of weekly cumulative NEE in the dry period was higher than the variation of weekly cumulative NEE of the wet period (Fig. 2b).

Higher anomalies in the measurement of NEE, GPP and RE were observed in 2014, 2015 and 2016, while lower anomalies in 2017 and 2018 (Fig. 3a, 3b and 3c). The intra-annual variation of NEE anomaly was higher during 2014 as compared to the other years. The NEE anomalies in 2014 to 2016 were ranging from 1.80 to -2.12 μmol$CO_2 m^{-2}s^{-1}$. A lower intra-annual variability of anomaly was observed in 2017 and 2018 for NEE, GPP and RE ranging from 0.62 to -1.08 μmol CO_2 $m^{-2}s^{-1}$, 0.8 to -0.96 μmol CO_2 $m^{-2}s^{-1}$and 0.8 to -1.74 μmol CO_2 $m^{-2}s^{-1}$, respectively. The GPP and RE monthly anomaly were observed to be higher during April and September of each year in comparison to the other months.

3.2. Principal component analysis and correlation coefficients (r)

The purpose of PCA analysis is to see the relationship between gaseous exchanges (NEE, GPP and RE) with weather variables like PAR, air temperature, soil temperature and precipitation on annual basis. The correlation circle of 2014-2018 data showed a projection of the initial variables in the factor space (Fig. 4a, b, c, d). In the year 2014, the variables PAR, air temperature, soil temperature, precipitation and RE were close to the centre and positively related. Results displayed in Fig. 4a for the two first principal components (PC; eigenvalues >1, 76% of total variance). The direction of GPP is opposite to RE which indicates negative correlation of these two variables (r close to -1). As the precipitation is not far from periphery, it may have little effect to the NEE, GPP, RE and other environmental variables. Similar pattern in the year 2015 and 2016 were observed for the first two principal components (PC; 71.8 and 74.4% of total variance respectively). In the year 2017 and 2018, for the two first principal components (PC; 68.8 and 72.8% of total variance respectively) NEE was closer to various weather variables as compared to rest of the years. Air, soil temperature, PAR and precipitation were highly correlated with NEE and RE in the year 2017 and 2018 compared to the other years.

Higher correlation was observed between NEE with GPP, RE and with other metrological variables during all the study period except 2017 (Fig. 5). NEE was highly and significantly correlated ($P<0.0001$) with PAR, precipitation, air temperature and soil temperature.

3.3. Auto-correlation and lagged correlation

In order to evaluate the degree of persistence in net carbon fluxes, from one year to the next the lag autocorrelation coefficients for each of weekly time series data were calculated and plotted in Fig. 6. The

temporal influence on NEE was persisted till 33 weeks, whereas for RE and GPP, it continued till 81 and 84 weeks, respectively. A steady decrease of correlation coefficient values for NEE, RE and GPP signifies that a particular week is influenced by its preceding week which was confirmed by the correlation value at 95% confidence interval. Almost a similar pattern of GPP and RE was observed which denotes that the effect of 1st week was pronounced up to 12 weeks and a discrete oscillatory pattern was observed.

Lagged correlation graphs are plotted for dry (Fig. 7) and wet seasons (Fig. 8) from 2014-2018 taking the gaseous exchange components such as NEE, GPP and RE with the weather variables like soil temperature, air temperature, PAR and precipitation. These correlations were more or less significant as per the variable and seasons taken into consideration. Though all the variables were not significant but had a similar pattern. In dry as well as wet season, NEE and GPP were significantly and negatively correlated with PAR, whereas RE was observed to be positively correlated with PAR although with different correlation coefficient, patterns and time scales.

4. Discussion

4.1. Temporal variation of CO_2 fluxes and meteorological variables

Temporal variation of NEE was higher in the year 2014, while it was lower and steadier in the year 2017, 2018. This may be primarily due to reduced rates of photosynthesis in the early growing season of 2017 and 2018 (Griffis et al. 2000). Annual net ecosystem CO_2 exchange varied from year-to-year as it is also controlled by solar radiation and temperature during the cropping season (Ohtani et al. 2005; Yu et al. 2008). Air and soil temperature variation showed a general trend round the year; they increased progressively as season changes from wet to dry. This is primarily because of the seasonal variation of insolation from the sun (Tsuang, 2003; Aires et al. 2004; Tsai et al. 2007). Temporal variation in air temperature is because of atmospheric absorption of solar radiation and trade of long-wave radiation with in the atmosphere. Temporal variation of soil temperature was recorded during both the crop growing seasons and fallows, this may be due to its daily variations in maximum temperature and minimum temperature (Sun et al. 2006). Conversely, in case of paddy fields, heat trapped in the water may control the soil temperature (Tsai et al. 2007). The water standing in rice fields from tillering to flowering, significantly lower the soil temperature in the DS than that in the WS. During the DS when the solar ray's reaches flooded fields, radiation is absorbed by the water surface and heat energy is transferred through water and soil by convection and conduction respectively (Mowjood et al. 1997). Therefore, the soil temperature becomes comparatively cooler when the fields are not flooded. In WS, the flooded rice field gets warm much slower than DS and release its heat energy very slowly than non-flooded fields. Mostly such condition prevails during early monsoon (June-July) and almost consistent up to late monsoon (October-mid November). This may be due to fact that the specific heat capacity of dry soil is five times lower than that of water (Foth, 1990). However, when flooded rice soils are drained, the insulation reaction of water is eliminated, making exposed soil surface cooler (Foth, 1990). Higher IAV

of PAR were observed in the year 2014, 2018 as compared to 2015 and 2016 which may be due to fluctuation in solar radiation (Jung et al. 2017) and high variability in precipitation that forms cloudy sky varied year to year. During WS the average seasonal PAR is lower than the dry season due to the prevalence of cloudy condition with the commencement of southeast monsoon in the WS (Cruz et al. 2013).

Annual variation of precipitation was observed higher in 2016 as compared to 2015. This may be due to prevailing of Indian summer monsoon during which most of the country receives more than 80% of its annual rainfall (Basu, 2007). Maximum precipitation was received during WS, which coincide with the south-west monsoon period in India. The monsoonal circulation is due to temperature differences between land and sea triggered by insolation (Huffman et al. 1997). The equatorial Indian Ocean anomaly, El Nino/Southern Oscillation (ENSO), is associated with inter-annual variability of monsoon rainfall or precipitation (Gadgil et al. 2003).

4.2. Influence of metrological variables on NEE

Increase soil temperature can also increase vegetative GPP by increasing the belowground carbon sink of photosynthetic assimilates (Baldocchi et al. 2001; Pumpanen et al. 2012). Plant and root respiration, which account, a major portion of RE of ecosystems are affected by temperature and growth stage of the plant (Semikhatova et al. 2009). The RE accounts about 33% of GPP under high light conditions and this relationship varies over seasons as soil and air temperature as well as change in plant phenology (Bubier et al. 1998). Furthermore, RE is affected by the presence of organic matter in soil (Moore et al. 1998). GPP and NEE are dependent on PAR and temperature which is strongly correlated to the seasonal development in the ecosystem and similar result has been also observed in our case (Vourlitis and Oechel, 1997). In our study, temporal variability in GPP is attributed to plant growth stage, variations in soil moisture, precipitation and PAR, similar to the observation by Griffis et al. 2000.

Air temperature affects both photosynthesis and respiration, thus it influences NEE, GPP and RE. Increasing temperature stimulates enzyme activity and accelerates the rate of both photosynthesis and respiration. The variation in rate of change in the photosynthesis and respiration of plants and ecosystems across years caused inter-annual variation in NEE (Wen et al. 2010). Besides increase in mean air temperature also extends the crop growing seasons, increase nutrient availability and change ecosystem water dynamics, which further influences IAV of NEE (Luo et al. 2010). Average soil temperature was higher in WS (July-October) compared to DS (January-May). At the same time, GPP decreases more quickly in WS compared to DS due to vegetation senescence and reduced incoming solar radiation at late growth stages. Annual NEE in DS are closely correlated with the soil temperature across years (Krishnan et al. 2006; Alberto et al. 2011; Keenan et al. 2014). Additionally, anomalies in soil temperature in WS significantly correlated with anomalies in GPP and NEE (Zhang et al. 2013).

Photosynthetically active radiation has more vital role than the other climate factors at local scales (Jung et al. 2011). Deviation in incident PAR causes expeditious changes in leaf photosynthesis (Wohlfahrt et

al. 2008). Due to this higher PAR at the mid to end of dry season correspond to higher NEE resulted from turbulent eddies transfer of CO_2 in and out of the plant canopy (Juang et al. 2007).

The difference in magnitude and quality of light form solar radiation causes the IAV of terrestrial GPP (Ichii et al. 2005). Diffuse radiation has a great impact on the IAV of NEE (Cox et al. 2013) in different ways. Increase in net radiation (NR), cloud cover largely during WS decrease direct radiation, and the frequency of light saturation and making the canopy photosynthesis more responsive to radiation changes (Farquhar and Roderick, 2003; Knohl and Baldocchi, 2008). The growing cloud cover upto a certain extent simultaneously decrease temperature, which in turn reduce the ecosystem respiration (Zhang et al. 2013). The overall canopy photosynthesis is increased by diffused radiation as it penetrates plant canopy more efficiently (Cheng and Porté-Agel, 2015).

For determining the IAV of NEE in agricultural ecosystems, the timing and frequency of precipitation are more important than yearly precipitation. Precipitation can affect the carbon cycle by its effects on soil water content (Knapp et al. 2008), soil temperature (Guo et al. 2015) and incident radiation (Nijp et al. 2015). Greater fluctuation of NEE in 2014 may attribute to the periodic precipitation events. However, the outcome of precipitation on NEE depends on the crop growing season. In WS, rainfall was associated with an increase in carbon uptake, while in the DS there was a net carbon loss. A maximum carbon assimilation rate was observed during July to September. The precipitation in WS followed by positive NEE values, showing similar GPP and RE response to increasing soil water content in the preceding months.

4.3. Output of statistical analysis to interpret the sources of inter-annual variability

Principal component analysis was used to find out the multivariate relationship among several environmental parameters (Chen et al. 2012). Air temperature was highly correlated with soil temperature throughout the study period. Besides it was also noticed that NEE was found to be highly correlated with soil and air temperature and PAR. Higher soil temperatures especially in wet season may increase the decomposition of soil organic matter which further increases dissolve organic carbon (DOC) in soil. The DOC formed in this process is then flushed from the soil system to the atmosphere (Piao et al. 2008; Vesala et al. 2010). RE was found to have positive correlation with soil, air temperature. Higher air temperature promotes photorespiration and rice drops their photosynthetic activities at higher air temperature (Crafts-Brander and salvucci, 2000) that caused reduced GPP and NEE because of increase in both autotrophic and heterotrophic respiration (Tseng et al. 2010). The relationship of PAR and NEE was already discussed in the previous section.

No significant correlation was established between NEE and precipitation throughout the study period as observed in the variable factor map of first two dimensions. Generally, changes in precipitation combined with changes in temperature to affect soil moisture, which is one of the factors for carbon exchange between land surface (soil, water & biosphere) and atmosphere (Keeling et al. 1996).

4.3. Lagged effect on biological and environmental variables

Seasonal variation in temperature and its anomalies may affect respiration more than photosynthesis (Piao et al. 2008; Yuan et al. 2009), and it may show lagged effects on consecutive seasons (Barford et al. 2001). In addition to the direct effects on photosynthesis and respiration, temperature change also cause the IAV of carbon fluxes by changing phenology of plant and growing season.

The findings from five years through different correlation studies suggest that climatic forcing and ecosystem responses play a crucial role in regulating the trend and magnitude of the IAV. In this study the annual NEE was found to be more influenced by the biological variables such as GPP and RE rather than the other weather variables. These results were also supported by Wohlfahrt et al. (2008), who reported the insignificant relationship between climatic drivers and atmospheric fluxes in annual time scale and the variation in annual NEE is due to biotic response rather than the weather variables.

In rice-rice low land ecosystem, the difference in IAV caused by climate variability was substantially smaller than that caused by changes of ecosystem responses due to the fact that five-year period is less to describe the climate anomaly. The relative importance of climate associated IAV decreased from GPP to RE and then NEE. The large fraction in NEE variation is described by biotic responses (55%), while the direct effect of environmental drivers was less (40%) (Richardson and Hollinger, 2007). Similarly, weak correlation observed in this study between weather variability and annual NEE was also reported by others (Wohlfahrt et al. 2008). They are also in favour of the hypothesis that IAV is mainly governed by indirect effects of weather variables that are altered by lagged changes in the ecosystem structure and physiological responses. The annual NEE was found to be less variable from the observed value because of the fact that changes in ecosystem response is counteracting the effect of climate variations.

5. Conclusion

A five-year long experiment using eddy covariance measurements in rice-rice ecosystem, inferred that NEE, GPP and RE anomalies are less in last two years of the study period which may be due to lower temperature anomalies in these years. The annual and seasonal variability of NEE, GPP and RE are associated differently with weather variables and of microclimates, PAR, precipitation, soil and air temperature. The temporal influence on NEE persisted till 33 weeks, whereas for RE and GPP for 81 and 84 weeks respectively. A steady decrease of correlation coefficient values for NEE, RE and GPP signifies that a particular week is more influenced by its preceding week. Climate anomaly in carbon cycle in lowland rice-rice system explained smaller IAV is due to short study period. In order to predict the future IAV of the terrestrial carbon cycle, it is necessary to understand the biological mechanisms through which anomalies in climate drivers cause the variation of NEE. Future studies should be focused on differential effects of climate anomalies on the physiological processes such as photosynthesis and respiration and of the relative importance of the timing of carbon uptake and its mobility by causing NEE fluctuations.

Moreover, independent approaches in time series data analysis, and assimilation to integrate data, modelling frameworks to predict future IAV in the terrestrial C cycle.

Declarations

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Ethics approval and consent to participate

Not applicable for this manuscript

Consent for publication

All authors have read the manuscript and agreed that the work is ready for submission to your journal, if suitable to your journal then issue of publication.

Availability of data and material

All the data will be provided on request.

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Authors' contributions

CK Swain, first author prepared the draft of the manuscript, A K Nayak, corresponding author gave the conceptual idea with thorough correction of the manuscript, Dibyendu Chatterjee helped in correction of the introduction part, Suchismita Pattanaik, Pratap Bhattacharyya, Vijayakumar S, Rahul Tripathi, helped in partly writing part of the manuscript, Sumanta Chatterjee, Mohammad Shahid, Nihar Ranjan Singh corrected the English grammar part.

Conflict of Interest

All authors have read the manuscript and agreed that the work is ready for submission and there is no conflict of interest.

References

Aires F, Prigent C, Rossow W (2004) Temporal interpolation of global surface skin temperature diurnal cycle over land under clear and cloudy conditions J Geophys Res: Atmos., 109(D4). https://doi.org/10.1029/2003JD003527.

Alberto MCR et al. (2011) Comparisons of energy balance and evapotranspiration between flooded and aerobic rice fields in the Philippines Agric. Water Manag., 98(9), 1417-1430.

Allaire JJ (2015) "Why Rstudio?" Rstudio.Com. Retrieved 12-15.

Amin, M., Amanullah, M., Akbar, A. (2014). Time Series Modelling for forecasting wheat production of Pakistan. J Anim Plant Sci., 24(5), 1444-1451.

Aubinet M, Vesala T, Papale D (2012) Eddy covariance: a practical guide to measurement and data analysis. Springer Science & Business Media,

Baldocchi D, Falge E, Wilson K (2001) A spectral analysis of biosphere–atmosphere trace gas flux densities and meteorological variables across hour to multi-year time scales Agr Forest Meteorol 107:1-27

Barford CC et al. (2001) Factors controlling long-and short-term sequestration of atmospheric CO_2 in a mid-latitude forest Science 294:1688-1691

Basu B (2007) Diurnal variation in precipitation over India during the summer monsoon season: Observed and model predicted Monthly weather review 135:2155-2167

Bhattacharyya P, Neogi S, Roy K, Dash P, Nayak A, Mohapatra T (2014) Tropical low land rice ecosystem is a net carbon sink Agric Ecosyst Environ189:127-135

Bhattacharyya P, Roy KS, Nayak AK (2016) Greenhouse gas emission from agriculture. Narendra Publishing house pvt. Ltd. New Delhi, India,

Bubier JL, Crill PM, Moore TR, Savage K, Varner RK (1998) Seasonal patterns and controls on net ecosystem CO_2 exchange in a boreal peatland complex Global Biogeochem Cycles 12:703-714

Chapin FS et al. (2006) Reconciling carbon-cycle concepts, terminology, and methods Ecosystems 9:1041-1050

Chatterjee D, Saha S (2018) Response of soil properties and soil microbial communities to the projected climate change. In: Advances in Crop Environment Interaction. Springer, pp 87-136

Chen G, Wang D, Hou Y (2012) The features and interannual variability mechanism of mesoscale eddies in the Bay of Bengal *Cont. Shelf Res* 47:178-185

Cheng W-C, Porté-Agel F (2015) Adjustment of turbulent boundary-layer flow to idealized urban surfaces: a large-eddy simulation study *Bound-Lay Meteorol* 155:249-270

Cox PM, Pearson D, Booth BB, Friedlingstein P, Huntingford C, Jones CD, Luke CM (2013) Sensitivity of tropical carbon to climate change constrained by carbon dioxide variability Nature 494:341-344

Crafts-Brandner SJ, Salvucci ME (2000) Rubisco activase constrains the photosynthetic potential of leaves at high temperature and CO_2 Proceedings of the National Academy of Sciences 97:13430-13435

Cruz S, Calado R, Serôdio J, Cartaxana P (2013) Crawling leaves: photosynthesis in sacoglossan sea slugs Journal of experimental botany 64:3999-4009

Falge E et al. (2001) Gap filling strategies for defensible annual sums of net ecosystem exchange Agr Forest Meteorol107:43-69

Farquhar GD, Roderick ML (2003) Pinatubo, diffuse light, and the carbon cycle Science 299:1997-1998

Foth H (1990) Soil physical properties Fundamentals of Soil Science 8th Eds John Wiley & Sons, Inc, New York:69-96

Gadgil M, Olsson P, Berkes F, Folke C (2003) Exploring the role of local ecological knowledge in ecosystem management: three case studies Navigating social-ecological systems: building resilience for complexity and change 189:209

Griffis TJ, Rouse W, Waddington J (2000) Interannual variability of net ecosystem CO_2 exchange at a subarctic fen Global Biogeochem Cycles 14:1109-1121

Guo M, Chai F, Xiu P, Li S, Rao S (2015) Impacts of mesoscale eddies in the South China Sea on biogeochemical cycles *Ocean Dyn* 65:1335-1352

Huffman GJ et al. (1997) The global precipitation climatology project (GPCP) combined precipitation dataset *Bull Am Meteorol Soc* 78:5-20

Husson F, Josse J, Le S, Mazet J (2007) FactoMineR: factor analysis and data mining with R R package version 1:04

Ichii K, Hashimoto H, Nemani R, White M (2005) Modeling the interannual variability and trends in gross and net primary productivity of tropical forests from 1982 to 1999 *Glob Planet Change* 48:274-286

Juang J-Y, Oren R, Kasibhatla P, Albertson J, Porporato A (2007) Investigating biosphere-atmosphere interactions from leaf to atmospheric boundary layer scales vol 67. vol 12.

Jung M et al. (2011) Global patterns of land-atmosphere fluxes of carbon dioxide, latent heat, and sensible heat derived from eddy covariance, satellite, and meteorological observations *J Geophys Res-Biogeo* 116

Jung M et al. (2017) Compensatory water effects link yearly global land CO_2 sink changes to temperature Nature 541:516-520

Kaimal JC, Finnigan JJ (1994) Atmospheric boundary layer flows: their structure and measurement. Oxford university press,

Keele L, Kelly NJ (2006) Dynamic models for dynamic theories: The ins and outs of lagged dependent variables Political analysis: 186-205

Keeling CD, Chin J, Whorf T (1996) Increased activity of northern vegetation inferred from atmospheric CO2 measurements Nature 382:146-149

Keenan TF et al. (2014) Net carbon uptake has increased through warming-induced changes in temperate forest phenology Nat Clim Chang 4:598-604

Knapp AK et al. (2008) Consequences of more extreme precipitation regimes for terrestrial ecosystems Bioscience 58:811-821

Knohl A, Baldocchi DD (2008) Effects of diffuse radiation on canopy gas exchange processes in a forest ecosystem Journal of Geophysical Research: Biogeosciences 113

Kolari P, Pumpanen J, Kulmala L-M, Nikinmaa E, Vesala T, Hari P Component CO_2 fluxes in a boreal Scots pine forest. In: Proceedings of the Finnish Graduate School" Physics, Chemistry, Biology and Meteorology of Atmospheric composition and Climate Change" workshop 22.-23.4. 2008, 2008. Finnish Association for Aerosol Research,

Krishnan P, Black TA, Grant NJ, Barr AG, Hogg ETH, Jassal RS, Morgenstern K (2006) Impact of changing soil moisture distribution on net ecosystem productivity of a boreal aspen forest during and following drought Agr Forest Meteorol 139:208-223

Le Quéré C et al. (2018) Global carbon budget 2018 Earth Syst. Sci. Data 10:2141-2194

Luo Q, Bellotti W, Hayman P, Williams M, Devoil P (2010) Effects of changes in climatic variability on agricultural production Clim. Res 42:111-117

Masseroni D, Facchi A, Romani M, Chiaradia EA, Gharsallah O, Gandolfi C (2015) Surface energy flux measurements in a flooded and an aerobic rice field using a single eddy-covariance system Paddy Water Environ 13:405-424

Mauder M, Foken T (2011) Documentation and instruction manual of the eddy-covariance software package TK3

Ministry of Environment F, India CCGo, Bank W (2018) Strengthening forest fire management in India. World Bank,

Moore B, Cheng SH, Rice J, Seemann J (1998) Sucrose cycling, Rubisco expression, and prediction of photosynthetic acclimation to elevated atmospheric CO_2 Plant Cell Environ 21:905-915

Mowjood MM, Ishiguro K, Kasubuchi T (1997) Effect of convection in ponded water on the thermal regime of a paddy field Soil Sci 162:583-587

Nijp JJ, Limpens J, Metselaar K, Peichl M, Nilsson MB, van der Zee SE, Berendse F (2015) Rain events decrease boreal peatland net CO_2 uptake through reduced light availability Global Change Biol 21:2309-2320

Novick KA, Biederman J, Desai A, Litvak M, Moore DJ, Scott R, Torn M (2018) The AmeriFlux network: A coalition of the willing Agr Forest Meteorol 249:444-456

Ohtani E, Hirao N, Kondo T, Ito M, Kikegawa T (2005) Iron-water reaction at high pressure and temperature, and hydrogen transport into the core Phys Chem Miner 32:77-82

Oksanen J, Blanchet F, Kindt R, Legendre P, Minchin P (2015) O'Hara RB, Simpson GL, Solymos P, Stevens MHH, Wagner H Vegan: Community Ecology Package 2:0-10

Papale D et al. (2006) Towards a standardized processing of Net Ecosystem Exchange measured with eddy covariance technique: algorithms and uncertainty estimation Biogeosciences 3:571-583

Piao S et al. (2008) Net carbon dioxide losses of northern ecosystems in response to autumn warming Nature 451:49-52

Pumpanen J, Heinonsalo J, Rasilo T, Villemot J, Ilvesniemi H (2012) The effects of soil and air temperature on CO_2 exchange and net biomass accumulation in Norway spruce, Scots pine and silver birch seedlings Tree Physiol 32:724-736

Rebmann C et al. (2018) ICOS eddy covariance flux-station site setup: A Review. Int Agrophys., 32(4), 471-494.

Reichstein M et al. (2005) On the separation of net ecosystem exchange into assimilation and ecosystem respiration: review and improved algorithm Global Change Biol 11:1424-1439

Richardson AD, Hollinger DY (2007) A method to estimate the additional uncertainty in gap-filled NEE resulting from long gaps in the CO_2 flux record Agr Forest Meteorol 147:199-208

R Studio (2015). Integrated Development for R. R Studio, Inc., Boston, MA. http://www.rstudio.com/.

Ruimy A, Jarvis P, Baldocchi D, Saugier B (1995) CO_2 fluxes over plant canopies and solar radiation: a review Adv Ecol Res 26:1-68

Ryan MG, Law BE (2005) Interpreting, measuring, and modelling soil respiration Biogeochemistry 73:3-27

Schulze ED et al. (2010) The European carbon balance. Part 4: integration of carbon and other trace-gas fluxes Global Change Biol 16:1451-1469

Semikhatova O, Ivanova T, Kirpichnikova O (2009) Respiration rate of arctic plants as related to the production process Russ J Plant Physiol 56:306-315

Smith P et al. (2010) Measurements necessary for assessing the net ecosystem carbon budget of croplands Agric Ecosyst Environ 139:302-315

Solomon S, Plattner G-K, Knutti R, Friedlingstein P (2009) Irreversible climate change due to carbon dioxide emissions P Natl Acad Sci 106:1704-1709

Sun D, Pinker RT, Kafatos M (2006) Diurnal temperature range over the United States: A satellite view Geophys. Res. Lett 33

Swain C et al. (2016) Net ecosystem methane and carbon dioxide exchange in relation to heat and carbon balance in lowland tropical rice Ecol. Eng 95:364-374

Swain CK et al. (2018) Greenhouse gas emissions and energy exchange in wet and dry season rice: eddy covariance-based approach Environ Monit Assess 190:423

Tanner CB, Thurtell GW (1969) Anemoclinometer measurements of Reynolds stress and heat transport in the atmospheric surface layer. Wisconsin Univ-Madison Dept of Soil Science,

Tsai J-L, Tsuang B-J, Lu P-S, Yao M-H, Shen Y (2007) Surface energy components and land characteristics of a rice paddy J. Appl. Meteorol 46:1879-1900

Tseng K-H, Tsai J-L, Alagesan A, Tsuang B-J, Yao M-H, Kuo P-H (2010) Determination of methane and carbon dioxide fluxes during the rice maturity period in Taiwan by combining profile and eddy covariance measurements Agr Forest Meteorol 150:852-859

Tsuang BJ (2003) Analytical asymptotic solutions to determine interactions between the planetary boundary layer and the Earth's surface *J Geophys Res* 108, 8608

Valentini R et al. (2000) Respiration as the main determinant of carbon balance in European forests Nature 404:861-865

Van Gorsel E et al. (2018) Preface: OzFlux: a network for the study of ecosystem carbon and water dynamics across Australia and New Zealand

Vesala HT, Vesala KM (2010) Entrepreneurs and producers: Identities of Finnish farmers in 2001 and 2006 J. Rural Stud 26:21-30

Vickers D, Mahrt L (1997) Quality control and flux sampling problems for tower and aircraft data J. Atmos. Ocean. Technol 14:512-526

Vourlitis GL, Oechel WC (1997) Landscape-scale CO_2, H_2O vapour and energy flux of moist-wet coastal tundra ecosystems over two growing seasons J. Ecol: 575-590

Webb EK, Pearman GI, Leuning R (1980) Correction of flux measurements for density effects due to heat and water vapour transfer *Q. J. R. Meteorol. Soc* 106:85-100

Wen X-F, Wang H-M, Wang J-L, Yu G-R, Sun X-M (2010) Ecosystem carbon exchanges of a subtropical evergreen coniferous plantation subjected to seasonal drought, 2003-2007 Biogeosciences 7

Wohlfahrt G, Hammerle A, Haslwanter A, Bahn M, Tappeiner U, Cernusca A (2008) Seasonal and inter-annual variability of the net ecosystem CO_2 exchange of a temperate mountain grassland: Effects of weather and management J. Geophys. Res. Atmos 113(D8).

Yamamoto J, Kagi H (2006) Extended micro-Raman densimeter for CO_2 applicable to mantle-originated fluid inclusions Chem. Lett 35:610-611

Yu L, Xin G, Gang W, ZHANG Q, Qiong S, Guoju X (2008) Heavy metal contamination and source in arid agricultural soil in central Gansu Province, China Int. J. Environ. Sci 20:607-612

Yuan W et al. (2009) Latitudinal patterns of magnitude and interannual variability in net ecosystem exchange regulated by biological and environmental variables Glob Change Biol 15:2905-2920

Zhang Q, Lei H-M, Yang D-W (2013) Seasonal variations in soil respiration, heterotrophic respiration and autotrophic respiration of a wheat and maize rotation cropland in the North China Plain Agr Forest Meteorol 180:34-43

Figures

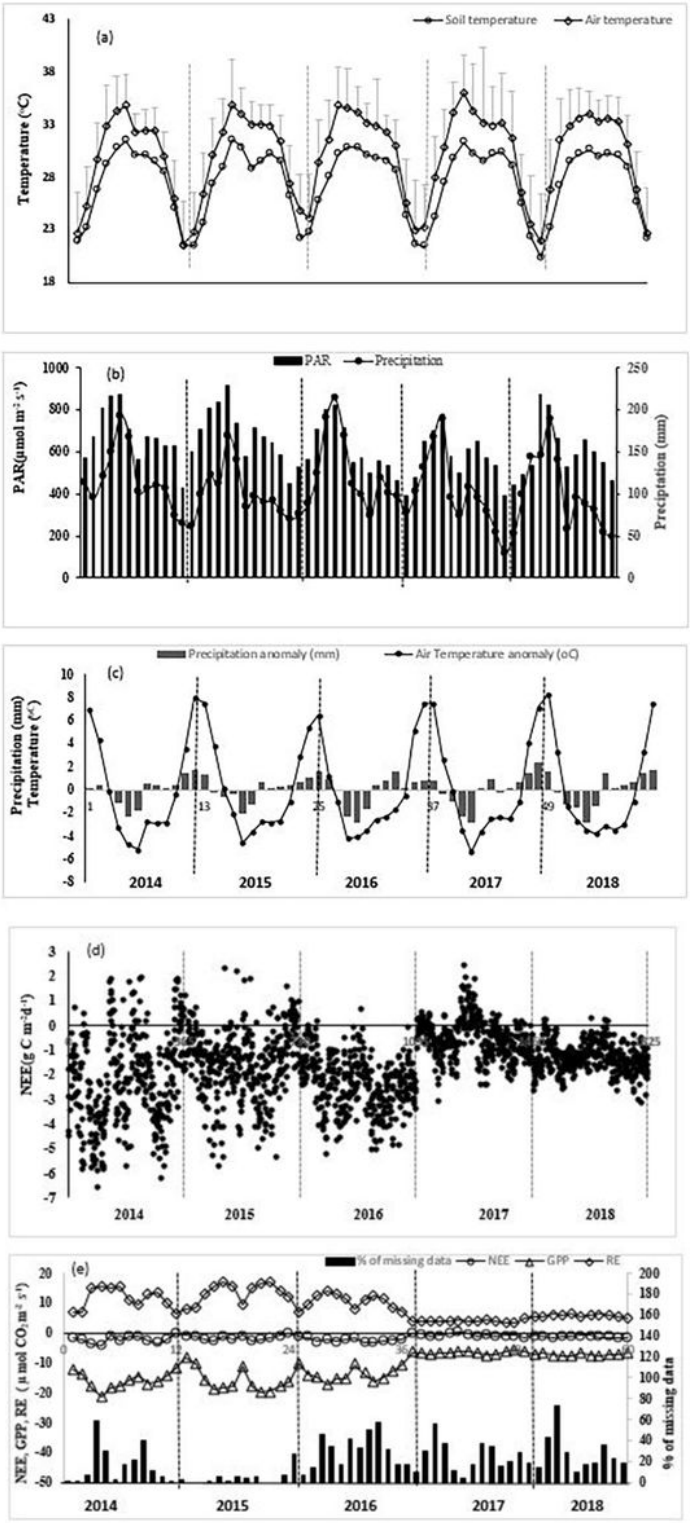

Figure 1

Monthly values of average air temperature (standard deviation) and soil temperature (a), photosynthetic active radiation (PAR) and cumulative precipitation (b), air temperature and precipitation anomalies (c) measured average NEE half hourly data (d), monthly values of average NEE, GPP, RE and % of missing data (e) during five different years.

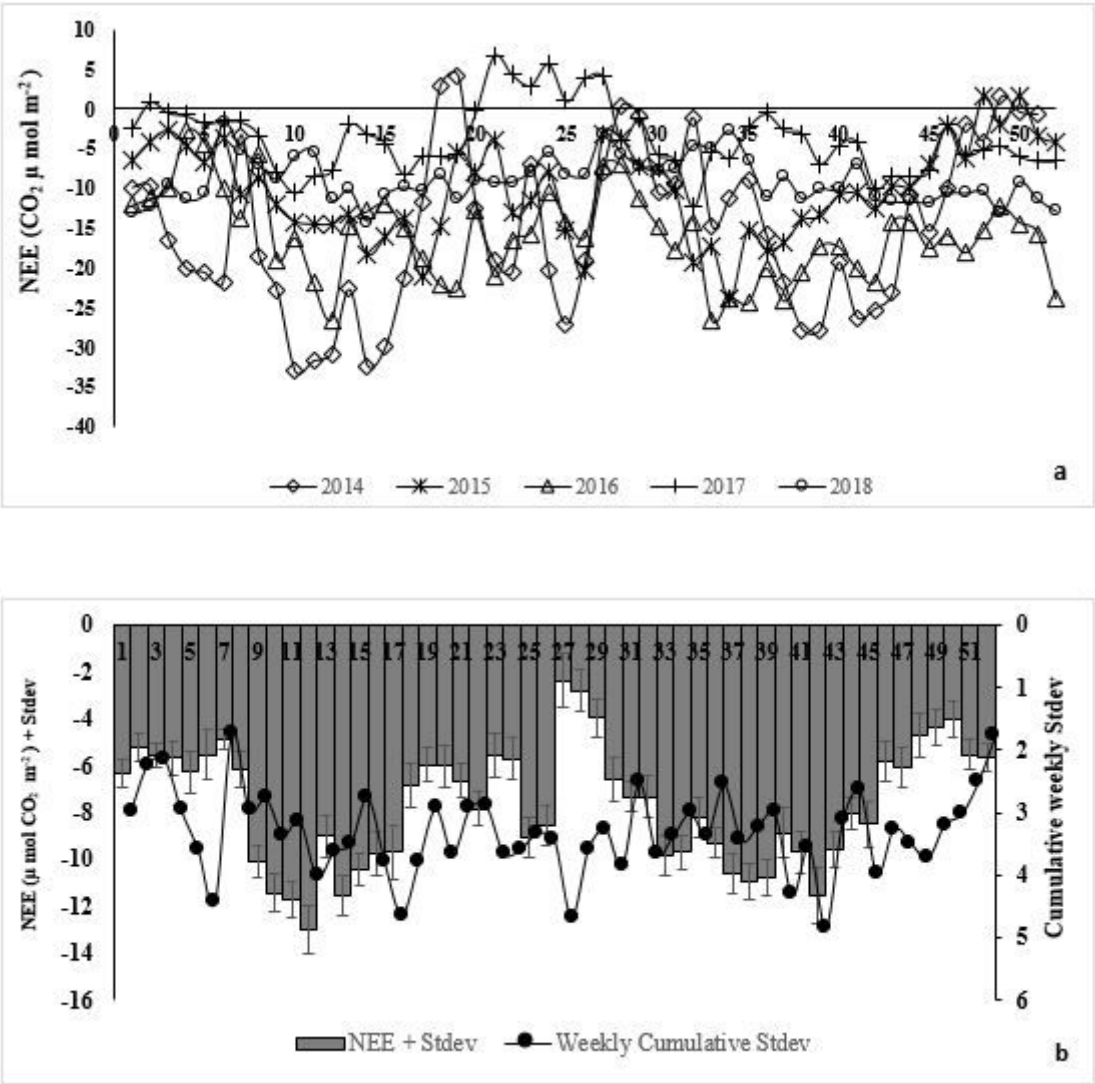

Figure 2

Yearly series of cumulative NEE for the period 2014–2018 (panel a); cumulative NEE averaged over the observation period and weekly variations in standard deviation (panel b).

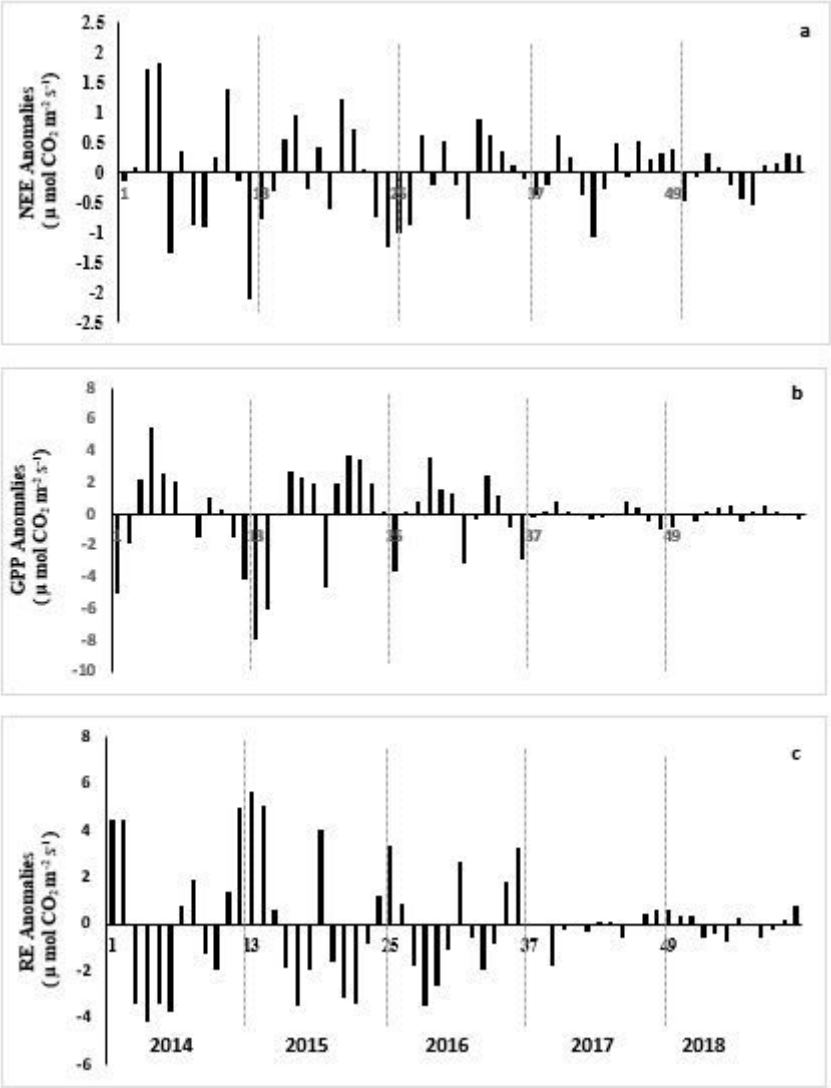

Figure 3

Monthly values of average NEE (panel a) and GPP and RE anomaly (panel b and c, respectively), obtained assuming variable climate change during the period of 2014-2018.

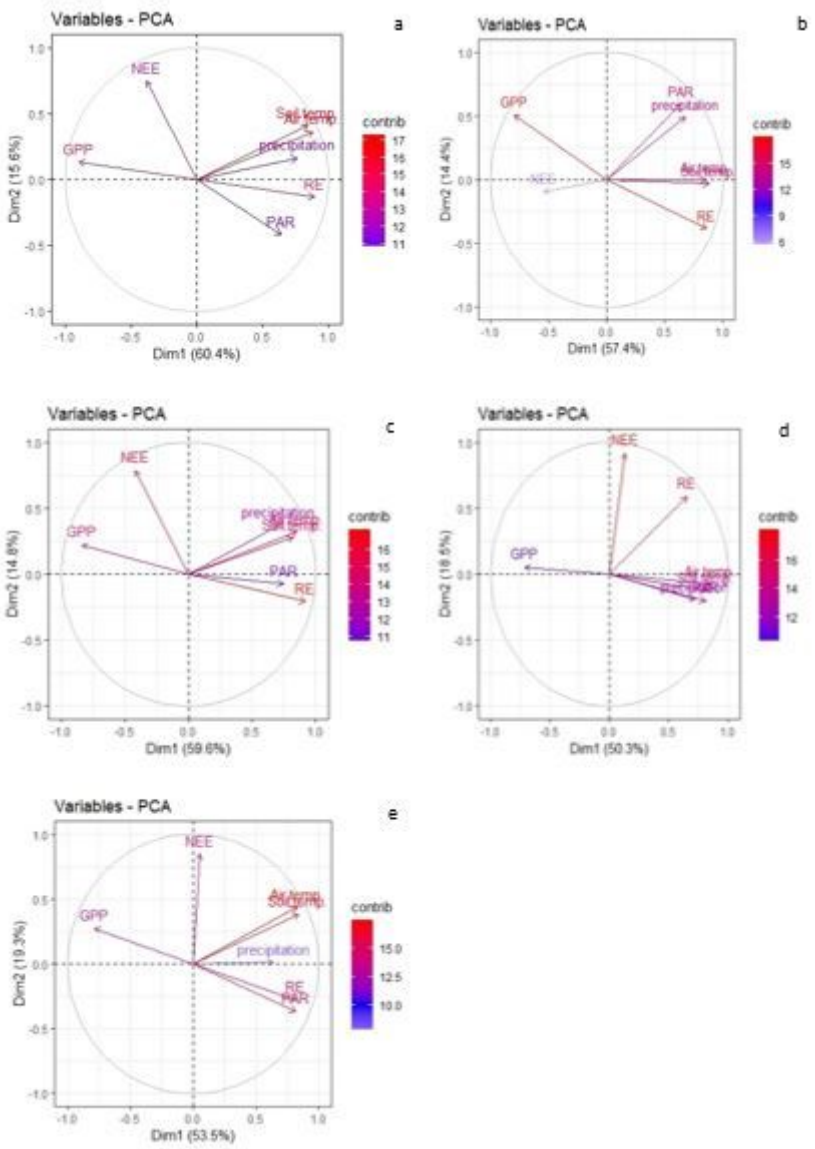

Figure 4

PCA analysis among different variables contribution such as in (a) 2014, (b) 2015, (c) 2016 (d) 2017 and (e) 2018 during the crop growing period.

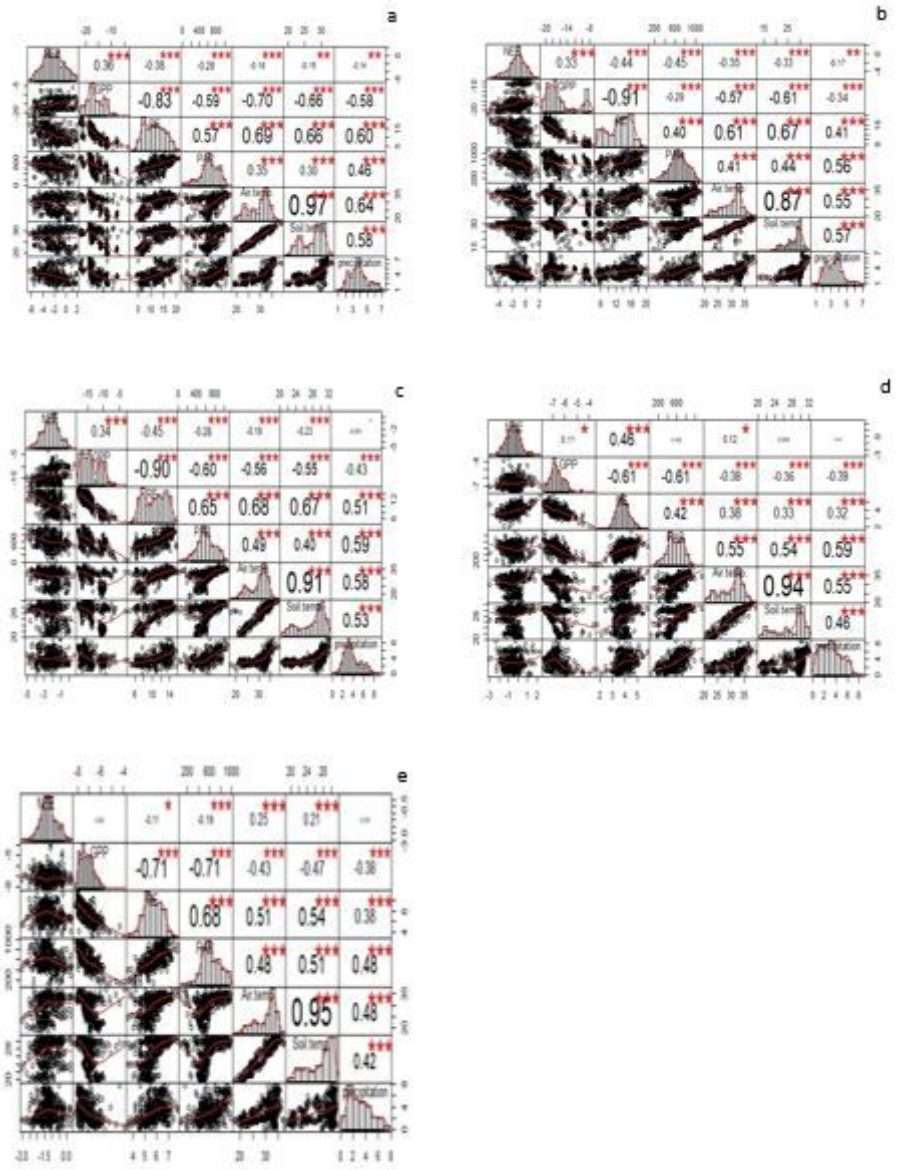

Figure 5

Correlation among different variables contribution such as in (a) 2014, (b) 2015, (c) 2016 (d) 2017 and (e) 2018 during the crop growing period.

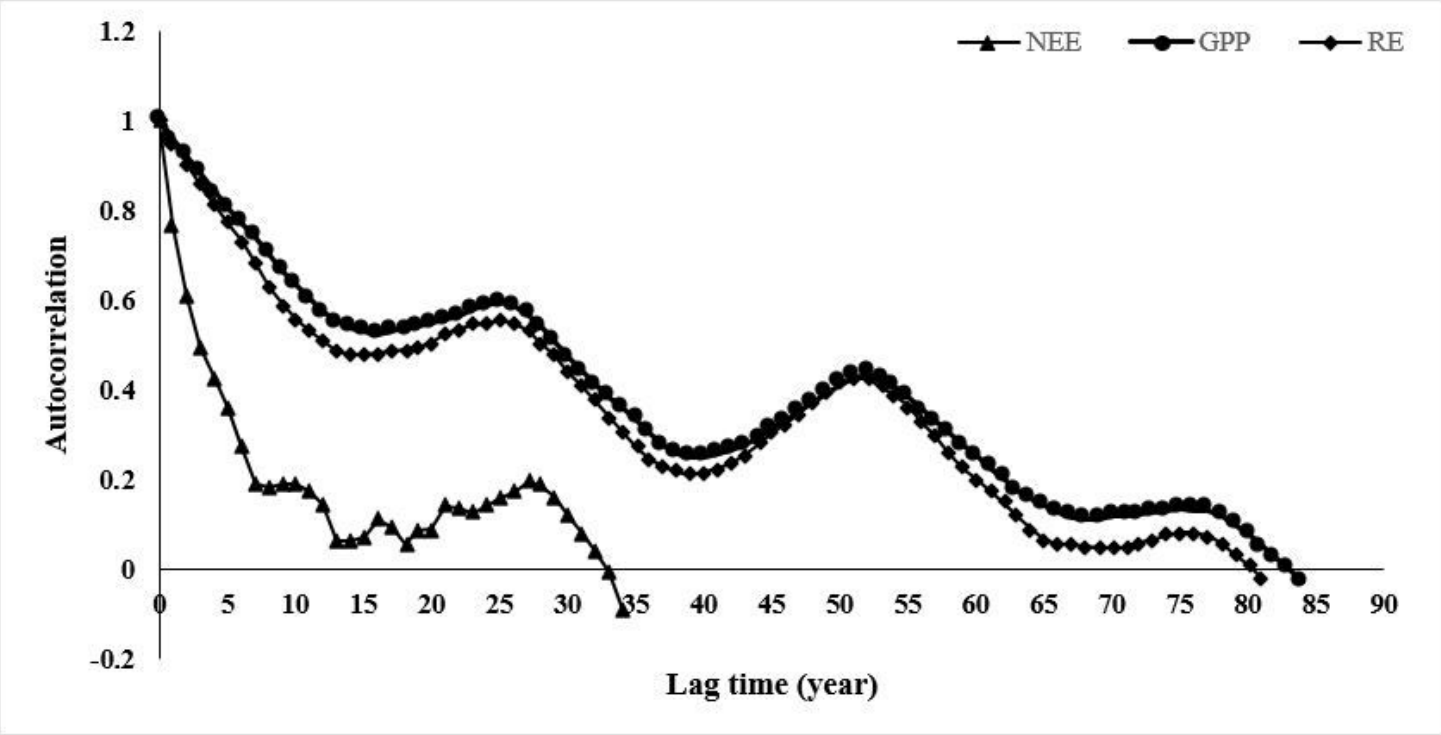

Figure 6

Auto-correlation functions for net ecosystem exchange, gross primary productivity and ecosystem respirationduring study period (2014-2018). To detect if the lagcorrelation values were significantly different from zero we performed a set of autocorrelation computations on a set of 260 weeks.

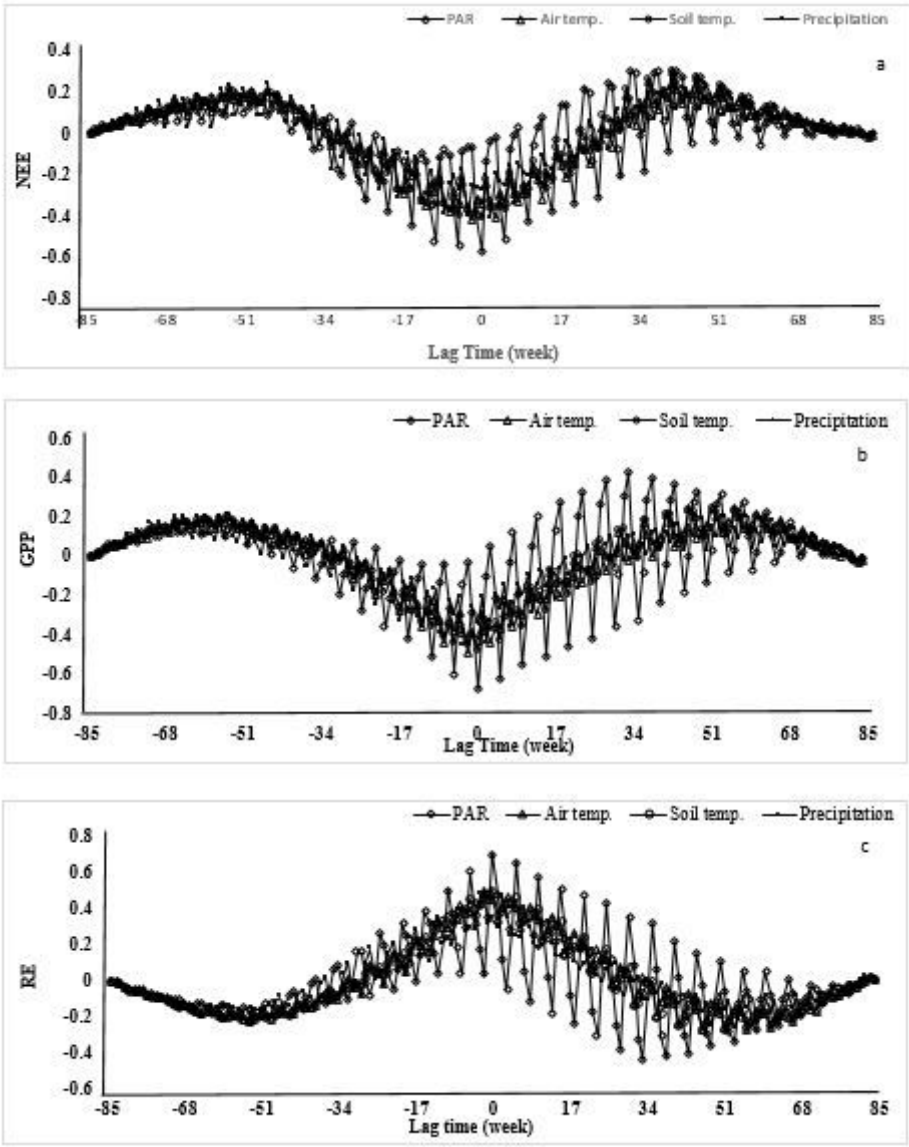

Figure 7

Lagged correlation periodical (a) NEE, (b) GPP, (c) RE and weather variables (i.e. PAR, Air temp., soil temp. and precipitation) averaged over weeks in the dry season during the period of year 2014-2018.

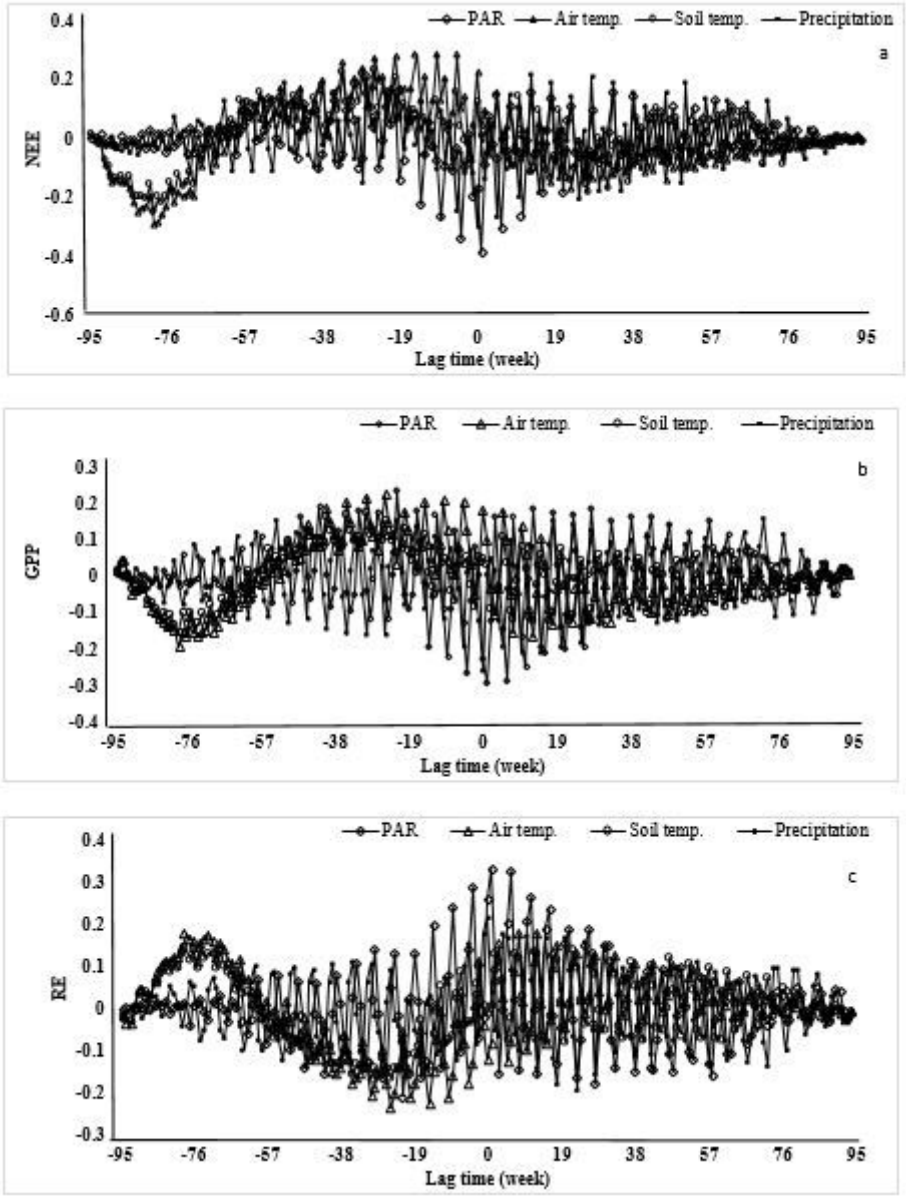

Figure 8

Lagged correlation periodical (a) NEE, (b) GPP, (c) RE and weather variables (i.e. PAR, Air temp., soil temp., and precipitation) averaged over weeks in the wet season during the period of year 2014-2018.