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Research papers

Importance of nutrient loading and irrigation in gross primary productivity trends in India

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ABSTRACT

Investigating the effects of various environmental factors on gross primary productivity (*GPP*) is crucial for quantifying the carbon exchange between the atmosphere and the terrestrial vegetation for managing climate change. Although it is well known that various natural and anthropogenic factors (e.g., climate change, agricultural activities, and atmospheric CO_2 concentration change) can alter *GPP*, their relative influences are not clearly understood in every region. In this study, we consider several factors and investigate their roles in increasing the *GPP* in large parts of India. We considered about three decades (1980s to late 2000s) of *GPP* data and use a regression based systematic approach to find out the most likely cause explaining the trends in India. This study suggests that the common suspects like CO_2 and climate may have limited influence on the *GPP* trends in India when compared to anthropogenic influences. Our results instead support the notion that *GPP* trends in India are mainly shaped by agricultural activities through nutrient loading ($R^2 = 0.68$) and irrigation ($R^2 = 0.1$). Overall, our study reveals the potential of agricultural activities in altering the carbon budget of a region.

1. Introduction

Photosynthesis driven gross fixation of CO_2 by terrestrial vegetation is known as gross primary productivity (*GPP*) (Anav et al., 2015; Heinsch et al., 2006; Running et al., 2000). Since *GPP* is one of the key components of carbon budget, there is a need to investigate the factors controlling it. Past studies have largely focused on global *GPP* trends and how they are influenced by various environmental factors, namely, precipitation, temperature, light intensity, and carbon dioxide concentration (Anav et al., 2015; Fensholt et al., 2012; Tian et al., 2016; Yang et al., 2015; Gilmanov et al., 2007; Yang et al., 2019). However, it is relatively less common to encounter region-specific analysis of *GPP* trends and their drivers. Particularly, *GPP* trends in India has not so far received adequate attention.

Over the years, India has been recognized for being a region with high inter-annual variability of *GPP* (Jung et al., 2011). Many studies have revealed significant *GPP* increase in parts of India in the last few decades using satellite based vegetation indices (Ahlström et al., 2015; Fensholt et al., 2012), which is concurrent with *GPP* increase many other regions of the world, e.g., Sahel in Africa (Prince et al., 2007) and Western Australia (Poulter et al., 2014). Such findings hold great importance for policy makers as India is one of the most populous countries in the world. Although multiple studies in the past have attempted to analyze the productivity trends and their drivers in India, the relative roles of natural as well as anthropogenic factors are not well understood (Bala et al., 2013; Nayak et al., 2015; Asoka and Mishra, 2015). In fact, most of the studies (Nayak et al., 2013; Asoka and Mishra, 2015; Sharma and Goyal, 2018) in the region have stressed more on the influence of meteorological drivers (namely precipitation, temperature, ENSO and Soil moisture) controlling the productivity. While a few other studies (Asoka and Mishra 2015; Bala et al., 2013) focused more on the anthropogenic effects, indicating that irrigation may have played a significant role in influencing the vegetation productivity. So there exists a disagreement whether climate change (Asoka and Mishra 2015) or anthropogenic factors (Bala et al., 2013) have led to the changes in vegetation productivity. Thus, the objective of the present study is to investigate how different factors have shaped the *GPP* trends in India during the time period from 1982 to 2008 using a different dataset and approach.

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2. Data and methods

The following datasets are used in the present analysis. The gridded *GPP* dataset was obtained from (Jung et al., 2011), which was created by upscaling the flux-tower data using the model tree ensemble technique. The *GPP* data has a temporal resolution of one month and a spatial resolution of $0.5° \times 0.5°$. The yearly *NDVI* data was obtained from a NASA data source (Didan, 2016) with resolution $0.5° \times 0.5°$. The monthly CO_2 was collected from terrestrial biosphere inter-comparison project (Huntzinger et al., 2012) with resolution $0.5° \times 0.5°$. Gridded daily average rainfall data (Pai et al., 2014) was obtained from Indian meteorological department (IMD) with $0.25° \times 0.25°$. Potential evapotranspiration was computed from IMD's $1° \times 1°$ resolution gridded daily (maximum, minimum and average) temperature data (Srivastava et al., 2009) following Hargeave's method (Hargreaves and Samani, 1985). We computed evapotranspiration caused due to natural factors (*ETn*) using the Budyko model (Budyko, 1974) as *GPP* is mainly a function of *ET*:

$$ETn = R\cdot(\phi\cdot tanh(\phi^{-1})\cdot(1 - e^{-\phi}))^{0.5} \tag{1}$$

Note that the Eq. (1) is valid only for a long timescale. *ETn* and *R* are, respectively, long-term average evapotranspiration and rainfall. ϕ is the dryness-index, which is the ratio of mean potential evapotranspiration (*PET*) to mean rainfall (*R*) for the time period.

It should be noted that agricultural activities have the potential to alter *GPP* trends due to irrigation and nutrient loading (Bondeau et al., 2007; Fisher et al., 2014). We thus obtained actual *ET* (*ETa*) data from Jung et al., 2011, who obtained the dataset by upscaling information from flux towers. *ETa* is expected to account for evapotranspiration from rainwater as well as from irrigation water. To investigate how anthropogenic nutrient loading influences *GPP*, we used the nitrogen threat index (*NTI*) dataset provided by Vörösmarty et al., 2010, which was prepared considering nitrogen concentrations at major river mouths and performing mass balance of nitrogen deposition (Green et al., 2004). The spatial resolution of the dataset is $0.5° \times 0.5°$. Note that *NTI* value of a region gives a measure of the change in nitrogen loading from pre-industrialized time to contemporary times (mid 1990s). However, the *NTI* dataset is expected to reflect well *Nr* concentration increase during our study period as agricultural intensification is a relatively recent phenomenon in most parts of India (Galloway et al., 2008). *NTI* varies from 0 to 1; higher values represent higher *Nr* loading rates, and vice versa. To check whether *GPP* changes are due to changes in evapotranspiration alone or also due changes in water use efficiency, we computed water use efficiency (*WUE*) by taking the ratio of *GPP* to *ETa*. Furthermore, state-wise forest cover percentage data were collected from Forest Survey of India, Dehradun (http://fsi.nic.in) to check if there are *GPP* trends caused due to change in forest cover. Furthermore, we also collected the state wise agricultural production (*PROD*), surface water irrigation (*SW*) and ground water irrigation (*GW*) data from 'Datanet India' (https://www.indiastat.com). Since, the data collected from indiastat were obtained for each administrative unit, we had to recompute data for the states where the administrative boundaries have changed.

All the above mentioned gridded datasets are processed to get spatially averaged information for administrative states of India, which is done for two reasons. i) Since many governmental policies capable of altering *GPP*, e.g. agricultural policies, are framed by the state governments in India, it would be appropriate to perform analysis considering spatial averaged information for the administrative states. ii) Spatial averaging will ensure reduction of errors in the data. Changes in *GPP* and the environmental factors were analysed after considering observations between the time periods 1982–1986 (A) and 2004–2008 (B) (see also Huang et al., 2015). Our main objective is to investigate *GPP* change between the time periods A and B how it is caused due changes in environmental factors. We follow a simple regression based approach and use our knowledge of the system to investigate the factors influencing the *GPP* trends. This type of analysis is often recommended when data availability is inadequate for implementation of more complex methods (e.g., Asoka et al., 2017; Bala et al., 2013; Huang et al., 2014; Liang et al., 2017). Since some of the regression equations are not capable of handling negative values, we introduce a change index (*CI*) that yields only positive values.

$$CI_X = \frac{X_B}{X_A + X_B} \tag{2}$$

CI_X in Eq. (2) is the *CI* for *X* which may represent or any of the environmental factors. Note that the change index was computed for all the environmental factors except *NTI*, as *NTI* ranges between 0 and 1. Similarly, *CI* is not computed for forest cover fraction as it ranges between 0 and 1. It should further be noted that the ground water irrigation data was not available for the entire timeline, thus we used the 1997–2002 data as a representative for the time period 'B'. We believe the usage of nearby period of the groundwater irrigation data is a valid assumption given the study is investigating the changes at relatively longer time duration (at inter decadal scale). This assumption has been discussed in more detail in the results and discussion section.

3. Results and discussion

The results indicate *GPP* has increased for many states in India during the study period from early 1980s to early 2000s (see Fig. 1). In fact, many of the states have witnessed steep increase in *GPP*. In particular, the CI_{GPP} for Rajastan is 0.60, which is equivalent to 48% increase in *GPP*. This is significant considering that Rajastan is one of the largest states in India with a geographical area of 880,000 km^2. CI_{GPP} is greater than 0.57 for Haryana, Maharashtra and Gujrat. Furthermore, CI_{GPP} is greater than 0.54 for the state of Uttar-Pradesh, Madhya-Pradesh, Karnataka, Andhra Pradesh, Tamil-Nadu, and Punjab. We observed that there is a spatial pattern in *GPP* increase across India; drier

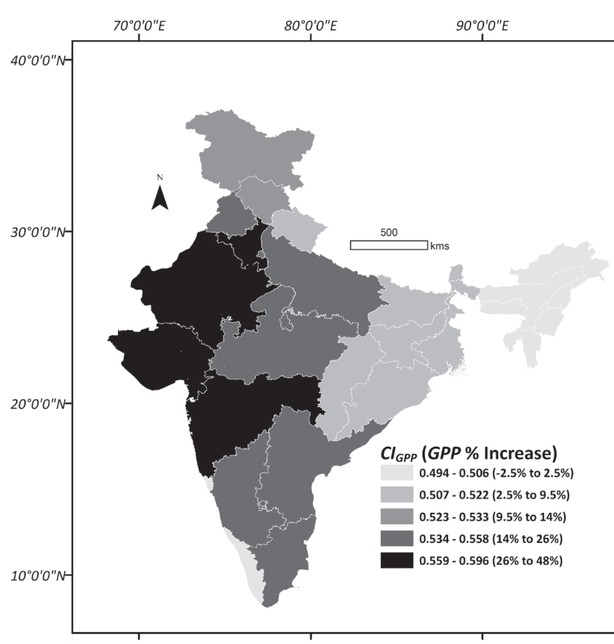

Fig. 1. Shows the change index of *GPP* (CI_{GPP}) from the period 1982–1986 to 2004–2008 period for 30 Indian states. The *GPP* increase has particularly been high for some of the northern and the western states. Moreover, there has been high increase in the *GPP* for central and southern Indian states as well. Interestingly the *GPP* has been stable for the northeastern region (e.g. Arunachal Pradesh and Mizoram) of India, where the human influence on the ecosystem is quite low due to higher forest percentage. For instance, Arunachal Pradesh and Mizoram with fairly high forest cover of 80% and 88% have seen only nominal changes in *GPP* of 2% and −3% respectively.

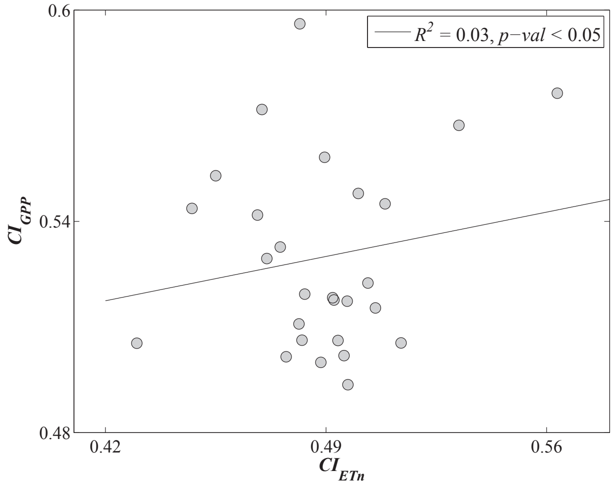

Fig. 2. Shows the plot between the change index of *GPP* (CI_{GPP}) and the changes in natural evapotranspiration (CI_{ETn}) for 30 Indian states. It should be noted that the has been budyko framework using the rainfall and the potential evapotranspiration data and it represents the water availability in the region based on the climatic conditions. It can be observed that there exist statistically insignificant ($R^2 = 0.03$) between both the variables. It suggests that the fluctuations in the natural climatic factors may not have caused the changes in *GPP* during early 1980 s to late 2000 s.

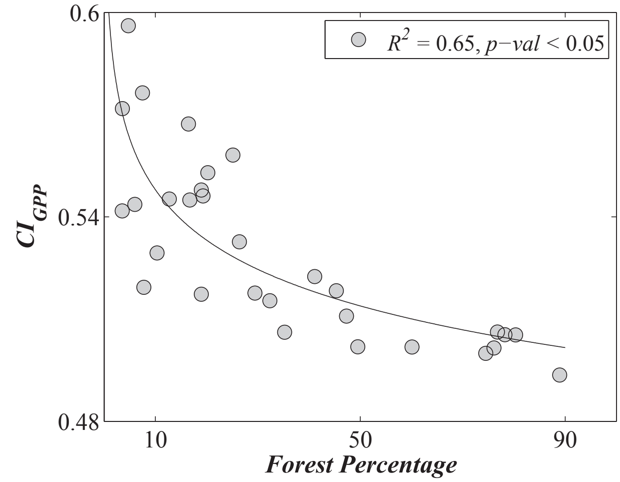

Fig. 3. Plot between change index of *GPP* (CI_{GPP}) and the percentage of forest cover in the state. We found a strong inverse relationship between CI_{GPP} and forest percentage in the state. Assuming that the forest percentage gives a good indication of less direct human influence in region, it can be suggested that the increase of *GPP* in India has been caused by human alteration of the environment.

states have witnessed higher increase in *GPP* as revealed by the fact that there is a strong relationship between CI_{GPP} and dryness-index (see Fig. S1 of the supplementary file). It is quite well known that drier ecosystems can especially be sensitive to climate change (mainly increased precipitation). For example, large-scale greening up was observed to occur due to increase in precipitation in Sahel region of Africa (Fensholt et al., 2012; Helldén and Tottrup, 2008). We thus investigated if the *GPP* trends in India are caused due to climatic changes by considering Budyko based evapotranspiration estimates (*ETn*). The rationale is that if every other factor remains unchanged, any change in *GPP* will be reflected by change in *ETn* due to climate change (Li et al., 2013; Yuan et al., 2010). Note that *ETn* given by the Budyko equation (eq. (1)) accounts for climatic factors only, and thus any climatic change will be depicted by the equation. However, we found CI_{ETn} (Fig. 2) having almost no relationship with CI_{GPP}, which supports the earlier finding by Fensholt et al., 2012 that precipitation and temperature changes don't explain the changes in *GPP* in India.

Many laboratory experiment-based as well as numerical analysis-based studies have shown that CO_2 concentration increase in the atmosphere can increase vegetation productivity (Bala et al., 2013; Gahlot et al., 2017; Roberntz and Stockfors, 1998). However, uncertainties still remain on how real world ecosystems respond to increase in atmospheric CO_2 concentration (Ellsworth et al., 2017; Friend et al., 2014; Medlyn et al., 2011; Norby et al., 2010). A recent study shows that *GPP* has not increased much in tropical regions although these regions have witnessed significant rise in CO_2 concentration (Van Der Sleen et al., 2015). Furthermore, some researchers have found that temperature increase can reduce *GPP* even when CO_2 concentration is increasing (Mooney and Zavaleta, 2016). They showed that CO_2 increase may not influence vegetation in a region where water and nutrients are limited. Not surprisingly lack of significant relationship between CI_{GPP} and $\boldsymbol{CI_{CO2}}$ observed in our study (Fig. S2 of the supplementary material) supports the notion of CO_2 not being a dominant factor behind *GPP* increase. This is expected as CO_2 concentration is not expected to exhibit significant spatial variation (see Fig. S2), and hence other factors must be responsible for any significant spatial variation of *GPP* trend observed in our study (Fig. 1).

An additional factor which may lead to large scale greening up in a region is change in the land-use pattern (mainly increase in agricultural area) (Saha et al., 2015). However, this factor may not have played a significant role in our case because cultivation-land area fraction in India has been fairly stable during the study period (Tian et al., 2014). Expectedly, we didn't find any significant relationship between change index of crop-area ($CI\_croparea$) and $\boldsymbol{CI_{GPP}}$ for the states in India (see Fig. S3 of the supplementary material). This is supported by a relatively recent study (Banger et al., 2015) which found that during the recent decades changes in the landcover has had very limited influence on *NPP*. Interestingly, our study suggests that *GPP* has not increased much in states which are dominated by forests, but states with low forest-cover fraction have seen steep increase in *GPP* (Fig. 3). In fact, there is an appreciably strong ($R^2 = 0.62$) correlation between CI_{GPP} and forest fraction of the state (Fig. 3), which indicates that the observed *GPP* trends in India are actually caused due to *GPP* from non-forested lands. It is likely that *GPP* trends in India being shaped by human activities, in particular agricultural activities (Banger et al., 2015; Nayak et al., 2015).

Thus, we investigated if agricultural activities have shaped the *GPP* trends in India. We observed (Fig. 4a) a strong positive correlation between CI_{GPP} and CI_{ETa}. Since the correlation between CI_{ETn} and CI_{GPP} is insignificant (Fig. 2), the relationship between CI_{GPP} and CI_{ETa} suggests some of *GPP* trends may be due to evaporation from irrigation water. However, irrigation activities alone may not be responsible for the *GPP* trends as nutrient application can also influence the vegetation production. It is thus not surprising that we also observed a strong correlation between CI_{GPP} and *NTI* (Fig. 4b). This indicates that the *GPP* trends in India are caused due to combination irrigation and nutrient loading. We thus need to be aware of the individual roles of irrigation and nutrient loading as there is a strong inter-relation between irrigation and nutrient loading on *GPP*, which is indicated by the correlation between CI_{ETa} and *NTI* (Fig. 4c). While irrigation increases *GPP* simply by increasing evapotranspiration, anthropogenic nutrient loading is known to increase *GPP* by improving water use efficiency (*WUE*) of plants (Tian et al., 2016; Xiao et al., 2013). We observed an appreciable correlation between CI_{WUE} and *NTI* (Fig. 4d), indicating that nutrient loading, along with irrigation, is responsible for the increasing *GPP* trends in many parts of India.

Now, for studying the influence of irrigation activities on *GPP* we plotted the changes in the irrigated area in India and the changes in *GPP*. Fig. 5a-b shows the plot between change index of *GPP* (CI_{GPP}) against the change index of surface water irrigated area (CI_{SW}) and

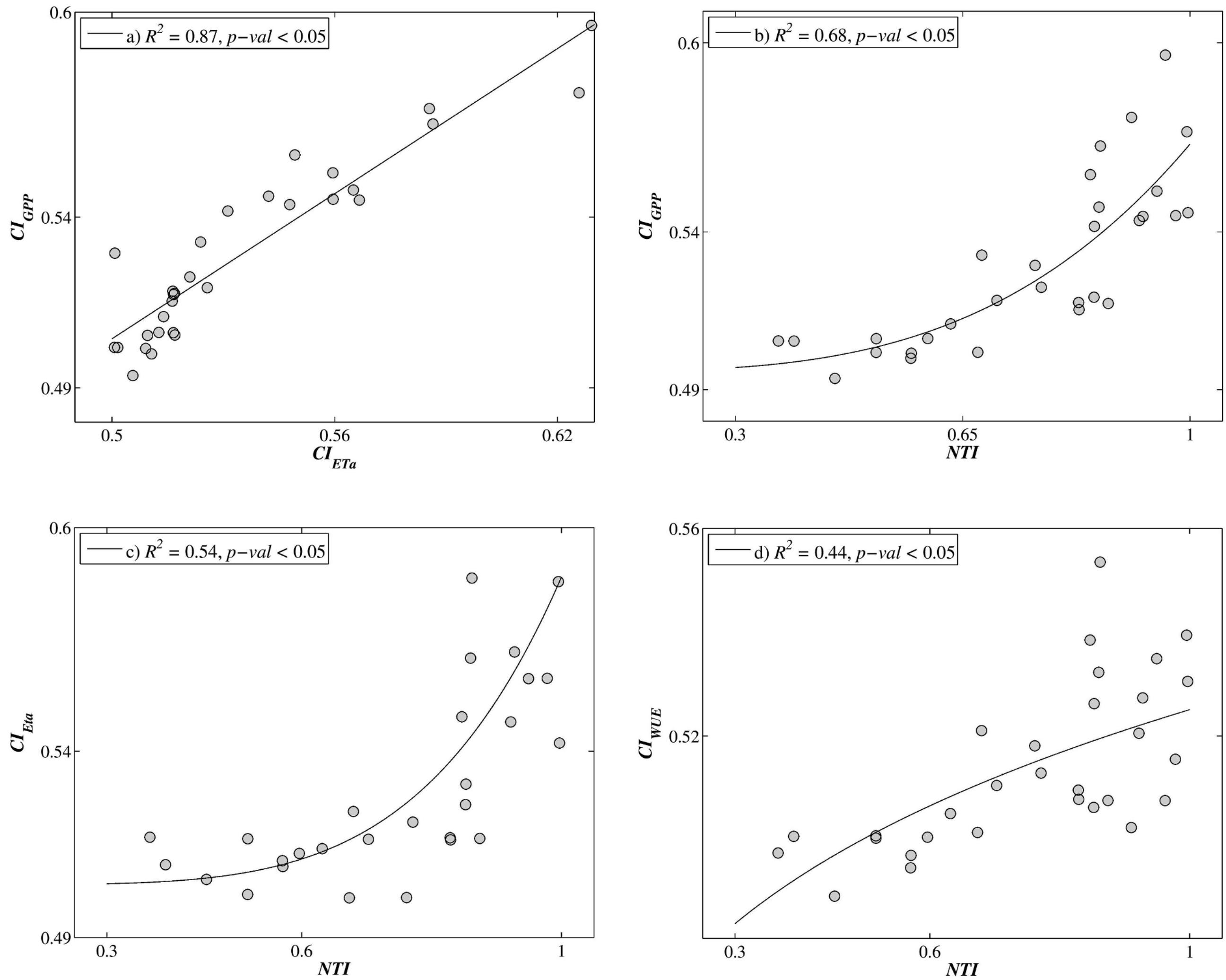

Fig. 4. a) Plot between the change index of actual evapotranspiration (CI_{ETa}) and the change index of *GPP* (CI_{GPP}). As expected there is a good relationship between CI_{ETa} and CI_{GPP}. This also suggests that *Eta* is capturing the changes effects of irrigation well. b) Plot between *GPP* (CI_{GPP}) and nitrogen threat index (*NTI*). Higher *NTI* indicates that there has been higher anthropogenic reactive nitrogen (*Nr*) alteration for the respective states. We can observe a significant powerlaw relationship between CI_{GPP} and *NTI*. Thus, it strongly suggests that the changes in *GPP* are due to human alteration of nitrogen cycle. c) Graph shows a good relationship between change index of *ETa* (CI_{ETa}) and *NTI*. d) Figure shows the plot between change index of water use efficiency (CI_{WUE}) and the nitrogen threat index (*NTI*). Statistically significant relationship between them suggests that the alteration of reactive nitrogen (*Nr*) may be one of the primary cause for the changes in *WUE*.

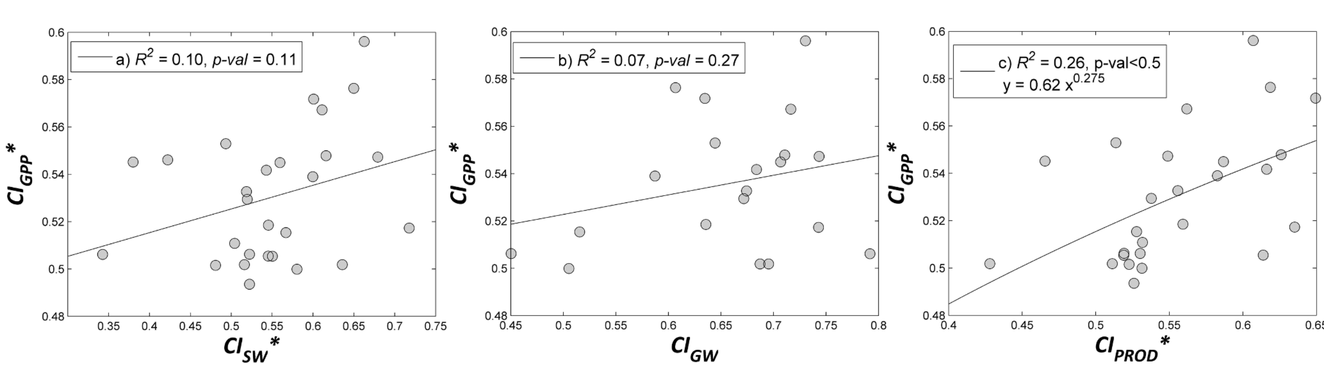

Fig. 5. a) Plot between the change index of *GPP* (CI_{GPP}) and the change index of surface water irrigated area (CI_{SW}). The relationship between the CI_{GPP} and CI_{SW} is not significant though there exists an increasing trend. It suggests that the increase in *GPP* in India has not been primarily driven by increased surface water irrigation. b) The figure shows the plot between change index of *GPP* (CI_{GPP}) and the change index of ground water irrigated area (CI_{GW}). The statistically insignificant relationship between CI_{GPP} and CI_{GW} suggests that even the irrigation by using ground water doesn't explain the changes in *GPP*. c) Plot shows a statistically significant relationship between change index of *GPP* (CI_{GPP}) and change index of agricultural production (CI_{PROD}). The power law relationship between CI_{GPP} and CI_{PROD} suggests that agricultural activity does explain some of the variation in *GPP*. Overall, since the influence of irrigation activity on *GPP* in India is not significant, it suggests that the changes in nutrient loading may have led to the increase in *GPP*. Please note that the star mark denotes that the variable has been recomputed to match the changes in the administrative state boundaries.

ground water irrigated area (CI_{GW}) respectively. The statistically insignificant relationship between CI_{GPP} and irrigation change indices (CI_{SW} and CI_{GW}) suggest that the role played by the irrigation activities in influencing the overall productivity may be limited. Fig. 5c shows the statistically significant power law relationship between the CI_{GPP} and changes index of agricultural production (CI_{PROD}). Since, agricultural production is closely related with the intensity of agricultural activities (which mainly includes irrigation and fertilizer application), the results supports the notion that *GPP* increase may have been caused by increasing intensity of agriculture. Furthermore, the weak relationship between irrigation change indices and CI_{GPP} suggests that the relative contribution of irrigation (w.r.t nutrient loading) towards increasing the productivity is less.

A potential limitation in the study could be due to the usage ground water irrigation data from nearby period (1997–2002) instead of the actual period 'B' (2004–2008) due to lack of data availability. We believe this approximation should have limited influence on the conclusion drawn from our study. Our study deals with the changes of *GPP* at a fairly long time scale (3 decades). Thus, the use of nearby (of about 5 years) data would not change overall relationship between CI_{GPP} and CI_{GW} significantly (see Fig. 5). Another supporting reason for the same is the relative stability of ground water irrigation at a larger spatial scale (see Asoka et al., 2017). I.e. it doesn't fluctuate abruptly when compared to other environmental factors influencing *GPP*.

4. Concluding remarks

GPP of an ecosystem represents its ability to transform atmospheric carbon dioxide, a greenhouse gas, into organic carbon, and hence study of *GPP* trends holds great relevance for policy makers. Several environmental factors control *GPP* of a region. A changing climate alters supply of water and (solar) energy to an ecosystem and thus altering its *GPP*, which is revealed by the changes in evapotranspiration rate. In this study, we used the Budyko model to assess the effect of changing climate on *GPP*. Another factor we considered is atmospheric carbon dioxide concentration, which influences *GPP* by controlling plant productivity. In our study we found neither the changing climate nor atmospheric CO_2 concentration change are responsible for the state-wise *GPP* trends in India. Our study instead supports the notion that agricultural activities are responsible for the *GPP* trends in India (Bala et al., 2013; Gahlot et al., 2017; Nayak et al., 2015) which is supported by the fact that there is an appreciable negative correlation between forest cover fraction and CI_{GPP}. This is a more plausible explanation given the increase in agricultural intensification with the adoption of modern agricultural practices during this time period (Fishman et al., 2016). Furthermore, we also found an appreciable relationship between *NTI* and CI_{GPP} ($R^2 = 0.68$). This suggests that the introduction of anthropogenic nitrogen into the system along with irrigation are responsible for the *GPP* trends in especially the northwestern and central parts of India. Thus, more investigations should be directed towards understanding how the anthropogenic nutrients are altering the ecosystems in the region.

CRediT authorship contribution statement

S. Patnaik: Conceptualization, Methodology, Software, Writing - original draft, Data curation, Formal analysis. **B. Biswal:** Supervision, Methodology, Writing - review & editing, Resources.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jhydrol.2020.125047.

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