Stochastic Environmental Research and Risk Assessment (2022) 36:1689–1701
https://doi.org/10.1007/s00477-021-02088-9

ORIGINAL PAPER

Does climate impact vary across time horizons? A time–frequency analysis of climate-crop yields in India

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Accepted: 4 September 2021 / Published online: 12 September 2021

Abstract
Climate change is a major concern the world over more so for a predominantly agrarian country like India. In this paper we analyze the time horizon dynamics of crop and climate variables at the regional level in India. We also analyze the co-movements of crop yields with temperature and rainfall to observe the coherence across heterogenous time horizons. We employ Bai-Perron structural break and Continuous wavelet transform methods on yearly data of seven crop yields and climate variables. Observed variables are analyzed from 1956 to 2010 for the un-divided state of Andhra Pradesh, India. Breakpoint analysis shows an increase of around 1.0° temperature with two observed break points. Rainfall depicts no systematic change with fluctuations being largely random. The framework of wavelets-based time–frequency analysis employed in this study captures climate and crop dynamics at heterogeneous time horizons, allowing one to study the impact of climate and crop yields at both short and longer time-horizons. Wavelet based coherence analysis exhibited significant co-movement between climatic and crop variables. Given shifts in climate patterns and subsequent shifts in co-movements across time horizons at the regional level, policy makers and crop scientists should design time specific and locally viable adaption and mitigation policies to tackle the impact of climate change on crops and livelihoods.

Keywords Climate Change · Structural break · Crop yields · Bai-Perron · Wavelets · Time horizon · Coherence · Co-movements

JEL Classification C13 · Q10 · Q15 · Q50 · Q54

1 Introduction

Climate change, attributed largely to the anthropogenic (Johns et al. 2003; Kaufman et al. 2011; Hansen and Stone 2016; Ambade et al. 2021) increase in greenhouse gas emissions is no longer a distant scientific prognosis but is a hard reality. The concentration of global atmospheric carbon dioxide, a greenhouse gas (GHG) largely responsible for global warming, has increased from a pre-industrial value of about 280–391 ppm in 2011. Similarly, the global atmospheric concentration of methane (CH_4), nitrous oxides (N_2O) and other important GHGs has also increased considerably (IPCC 2013). Adequate evidence suggesting change in climatic parameters can be observed from increased global average temperatures and change in rainfall patterns during the twentieth century. Eleven of the twelve years between 1995 and 2006 rank among the twelve warmest recorded since 1870 (IPCC 2007).

Climate variability is a major concern for India given its size and demographic dependence. Studies show a marked rise in temperature over the last century in India both at the national and regional level (GOI 2010; Kothawale et al. 2010; Patni et al. 2020). The annual mean temperature during 1901–2019 showed an increasing trend of 0.61 °C/100 years, with significant increasing trend in maximum temperature at around 1.0 °C per 100 years (GOI 2020). This is found to be mainly contributed by the post-monsoon and winter seasons, even as the monsoon

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temperatures do not show a significant trend (Kumar et al. 1994; Mondal et al. 2015). However, rainfall fluctuations in India have been largely random over a century with no systematic change detected in summer monsoon season (Prasad and Kochher 2009). Yet at regional level rainfall has exhibited changes in the last century, with areas around West coast, North Andhra Pradesh, and North-West India found to exhibit increasing trend and East Madhya Pradesh, Orissa and North-East exhibiting declining trend (Kumar et al. 1992; GOI 2008).

Estimates show India's climate to become warmer, with a predicted increase in annual mean maximum and minimum temperature of 0.7 °C and 1.0 °C over land in the 2040s with respect to the 1980s and increase of 1–1.4 °C and 2.23–2.87 °C area average annual mean warming by 2020 and 2050 respectively (Lal et al. 1995, 2001). The temperature rise is likely to be much higher during the winter (rabi) rather than in the rainy season (kharif). The warming is more pronounced over land areas with a maximum increase over Northern India. These changes are likely to increase the pressure on developing countries like India (Rosenzweig and Parry 1994; Mendelsohn 2008) given their greater dependence on agriculture, in addition to the ongoing stresses of yield stagnation, competition for land, water and other resources and globalization (Paroda and Kumar 2000).

The state of Andhra Pradesh, now divided into two separate states, namely (i) Telangana and (ii) Andhra Pradesh, was the fifth largest in the country both in terms of population (84.6 million) and geographical area (27.4 million hectares). The undivided state of Andhra Pradesh has a tropical climate with moderate to subtropical weather and exhibits diverse climatic patterns across different agro-climatic zones (Padakandla 2020). Humid to semi humid conditions prevail in the Coastal areas while arid to semi-arid situations are prevalent in the interior parts, particularly Rayalaseema and some districts of Telangana (Government of Andhra Pradesh 2011b). The state receives rainfall from South-West (June–September) and North-East (October- November) monsoon. However, there is large variation in the distribution as coastal areas generally receive the highest rainfall, while regions of Rayalaseema and Telangana fall in the precarious and modest rainfall category (Government of Andhra Pradeskh 2011a). The undivided state of Andhra Pradesh is primarily agrarian in nature and is the third largest producer of rice and groundnut and second largest producer of cotton and sunflower. The impact of climate on this state is more intense not only because of its dependence on agriculture but also due to diverse impact across different climatic regions (Padakandla 2020).

The effect of climate is heterogeneous in both spatial and temporal dimensions (Gornall et al. 2010; Leng and Huang 2017; Zhao et al. 2017; Kukal and Irmak, 2018; Kumar and Kaur 2019; Chang et al. 2019; Kurths et al. 2019; Ray et al. 2019). It is well documented in literature that Indian agricultural growth is highly dependent on the spatial and temporal distribution of monsoon rainfall and temperature (Kumar et al. 2004; Asada and Matsumoto 2009; Shukla et al. 2018). In view of the above, we analyze the heterogeneous impact of climate change on crop yields in the undivided state of Andhra Pradesh, India over different time horizons.

The rest of the article is structured as follows. Section 2 provides a brief review of literature and research motive for the study. In Sect. 3, we present the methods used for analysis along with the data sources. The results are discussed in Sect. 4 and the concluding remarks are provided in Sect. 5.

2 Review of literature

There is a plethora of literature on the dynamics of climate and crop yields and its impact. Though some experimental and simulation studies demonstrate elevated CO_2 in the atmosphere help crops favorably (Baker et al. 1992; Kimball et al. 2002; Krishnan et al. 2007), related impact of increased temperature, changing patterns of rainfall and extreme weather events is likely to increase risks in crop production (Matthews et al. 1997; Parry et al. 2004; Fofana 2011; Pal and Mitra 2018; Nath and Mandal 2018; Guntukula and Goyari 2020). Apart from the physical impact of climate on crop yields (Selvaraju 2003; Gupta et al. 2014; Zhang et al. 2017), there is a fair amount of literature on monetary impact of climate on yields (Kumar and Parikh 2001; Kumar 2009; Guiteras 2009; Fishman 2012). Studies have also estimated impact of climate change on land value or net revenues (Mendelsohn et al. 1994; Massetti and Mendelsohn 2011; Mishra et al. 2016).

The method of breakpoint analysis, primarily to test for stationarity and instability in time-series data is extensively used in financial and economic analysis (Kim et al. 2005; Bajo-Rubio et al. 2008; Chen and Zivot 2010; Kar et al. 2013). However, studies on crop-climate dynamics are limited, especially in the context of India. Arora et al. (2005) and Jhajaria and Singh (2011) employed non-parametric test to detect monotonic trends in annual average and seasonal temperature over India and North-East India respectively. Alternatively, Paul et al. (2014) employed CUMSUM and Chow test to discover an observed breakpoint around 1970–1980 both at the country and regional levels. Similarly, Mondal et al. (2015) employed Mann-Kendall test and Sen's slope to analyze the trend magnitude and Mann-Whitney-Pettitt to test probable break point detection in the series.

Wavelet based analysis of climatic time series is relatively a new area of study where multiresolution analysis is applied to climatic variables at varying time horizons. For example, Zhang et al. (2014) using Haar wavelets, discover regime shift in Arctic oscillation. Similarly, Morlet wavelet is used to study the phenomenon of runoff in Yangtze River at varying time horizon by Qian et al. (2014). In the same vein, Xu et al. (2009) decomposes the time series weather data into multiple time horizons to study the impact of climate change in the Tarim river basin of China. More recently, Yang et al. (2021) and Abahous et al. (2021) used wavelet-based methods to analyze climatic impact on crop yields in inner Mongolia and northwestern Africa, respectively. In the Indian context, Ratinasamy et al. (2019) employed wavelet coherence to detect significant interannual and interdecadal oscillations in monthly precipitation extremes across India and their teleconnections to three prominent climate indices.

Survey of existing literature show majority of studies either analyzed time series dynamics of climate and crop variables either independently or examined their relationship only in time domain, whereas studies examining the simultaneous localization of information from both time and frequency domains are practically non-existent. Given that there is increasing variability of climate across spatial and temporal horizons, the present analysis will bridge the gap in the existing literature by analyzing the climatic impact on crop yields across time horizons.

3 Materials and methods

3.1 Structural change

Tests for parameter instability and structural change in regression models have been an important part of applied econometric work dating back to Chow (1960) who tested for regime change at a prior known date using an F-statistic. This was further modified by Quandt (1960), to relax the requirement that the candidate break-date be known and consider the F-statistic with the largest value over all possible break-dates. Later, Andrews (1993) and Andrews and Ploberger (1994) derived the limiting distribution of the Quandt and related test statistics. Bai (1997) and Bai and Perron (1998, 2003) provide theoretical and computational results that further extend the Quandt-Andrews framework by allowing for multiple unknown breakpoints.

We employed Bai Perron test to identify the trend and breakpoints across different climate and crop yields. The methodology to detect multiple breakpoints follows the work by Bai and Perron (1998). The data generating process is given by

$$Y = X\beta^0 + {}^-Z^0\delta^0 + U \tag{1.1}$$

where the true value of the coefficient at time t is given by the subscript *0*. The data is divided into m partitions and the following global minimum is computed

$$\left(\widehat{T_1},\ldots\ldots\widehat{T_2}\right) = argmin_{T_1,\ldots\ldots\ldots,T_m} S_T(T_1,\ldots\ldots,T_m) \tag{1.2}$$

where S_T represents the sum of squared residuals, and is given by

$$S_T = \sum_{i=1}^{m+1} \sum\nolimits_{t=T_{i-1}+1}^{T_i} [y_t - x'\beta - z_t'\delta_i]^2 \tag{1.3}$$

The next procedure in the algorithm is to compute the statistic is derived from the sup F test as detailed in Andrews (1993). The null hypothesis of no breaks is checked against the alternative of m = k breaks after computing the following statistic.

$$F(\lambda_1,\ldots\ldots,\lambda;q) = \left[\frac{T-(k+1)q-p}{kq}\right]\left[\frac{\widehat{\delta}'R'\left(R\left(\overline{Z}M_xZ\right)^{-1}R'\right)^{-1}R\widehat{\delta}}{SSR_k}\right] \tag{1.4}$$

where.

$$T_t = [T\lambda_i]$$

$$(R\delta)' = (\delta_1' - \delta_2', \ldots, \delta_k' - \delta_{k+1})$$

$$M_X = I - X(XX)^{-1}X$$

In the above algorithm, an assumption is made at the number of breaks ($m = 0,1,\ldots,k$) in the first stage. Subsequently, the time series is divided into m segments (T_1, …, T_m) which minimizes the sum of squared residuals, S_t. The final step in the algorithm involves the computation of an F test which compares the assumption of no breaks with the occurrence of k breaks. The said number of breaks as assumed in the first step is said to occur if the computed statistic is above the critical value.[1] All computations were implemented in R statistical environment using the algorithm developed by Zeileis and Kleiber (2005).[2].

Alternatively, we employ continuous wavelet transform method to test the robustness in the trends and breakpoints and observe the co-movements between crop and climate variables across different time horizons. The advantage of

[1] Refer Bai and Perron (2003) for the details of algorithm that identifies the break dates.

[2] This package implements a large collection of methods for the analysis of structural change, as well as methods for the dating and monitoring of structural breaks. Both the R system and the struchange package are freely available under the terms of the GNU General Public License (GPL) from the Comprehensive R Archive Network (CRAN), at http://CRAN.R-project.org/.

wavelet method is that they can decompose the yearly series into different time horizons starting with yearly. For yearly time horizon the wavelet analysis gives results that is also seen in structural break analysis, but the drawback of structural break analysis is that it cannot give information for higher time horizons i.e. more than two years. Analysis over the time horizon is basically the vantage point of this study. Since climate is a long run phenomenon and its impact on crop yields occur over different long-run time horizons, we use wavelets to decompose the trend and to measure the impact. The detailed methodology is explained in the following section.

3.2 Wavelets

Wavelets are small waves,[3] with varying oscillations, that vanish after some time interval. Wavelet analysis allows one to decompose the time series data into both time and frequency components simultaneously. This is advantageous as traditional time-series methods cannot capture frequency information which is related to time-horizon of study. Therefore, wavelets can filter data based on components from varying time-horizon starting with smallest horizon, or short-run, and capturing information from longer time horizons too. Computations are based on the continuous wavelet methodology as described in Grinsted et al. (2004) and Bhandari and Kamaiah (2019).

3.2.1 Continuous wavelet transform

The estimator used to analyze co-movements between two time-domain variables, is given by wavelet coherence which is based on the continuous wavelet transform. A wavelet is a real valued function $\psi(.)$ defined on $\mathbb{R}$ such that

$$\int_{\mathbb{R}} \psi(t)dt = 0 \tag{2.1}$$

$$\int_{-\infty}^{\infty} |\psi(t)|^2 dt = 1 \tag{2.2}$$

Wavelet analysis is performed by choosing a reference wavelet known as *mother wavelet* $\psi_{b,s}$, which is defined as

$$\psi_{b,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-b}{s}\right) \tag{2.3}$$

where $s \neq 0$ and b are real constants. The parameter s is the scaling parameter (used to determine window widths), whereas the parameter b denotes the translation parameter (used to determine the position of the window).

The "*continuous wavelet transform*" (CWT) of a time signal $x(t)$ is defined as

$$W^X(b,s) = \int_{-\infty}^{\infty} x(t)\,\overline{\psi}_{b,s}(t)\,dt \tag{2.4}$$

provided the following *admissibility condition*[4] is satisfied

$$C_\psi = \int_{-\infty}^{\infty} \frac{|\Psi(\omega)|^2}{|\omega|} d\omega < \infty \tag{2.5}$$

where $\Psi(\omega)$ is the Fourier transform[5] of the mother wavelet $\psi_{a,b}(t)$. The square of the absolute value of the CWT is known as the wavelet power and is given by $\left|W^X(b,s)\right|^2$, where the complex argument of $W^X(b,s)$ gives the local phase. Analogous to the boundary problem encountered in discrete wavelet methods, CWT too suffers from edge effects as the transform is incorrectly computed at the initial and end points of the time-series. Edge effects can be taken into consideration by introducing a Cone of Influence (COI). It is the area in wavelet spectrum where wavelet power at the edges generated by some discontinuity has fallen by a magnitude of e^{-2} of the edge's value.

Wavelet coherence diagram helps one to distinguish between significant short and long-term correlations. Information from timescales ranging from around 2–16 years is given in the left vertical axis of coherence plot. Morlet wavelet is used as the "mother wavelet" in computing wavelet coherence and the significance is determined by Monte Carlo methods. The cone of influence (COI), where the coherence map is affected by boundary problem, is shown in a lighter shade. Statistically significant areas in the coherence plot, with 5% significance level, are denoted by bold black borders. The color-coded coherence map reveals strongest power at regions with red color whereas blue regions reveal low power.

3.3 Data sources

State level data on temperature (maximum, minimum and average temperature), rainfall (average rainfall, South-West monsoon rainfall and North-East monsoon rainfall) and yield of seven principal crops (rice, jowar, maize, cotton, groundnut, sugarcane and tobacco) from 1956 to 2010 is used for the analysis. Crop yield data is collected from various volumes of season and crop reports of Andhra Pradesh. Data on rainfall is collected from "A profile of rainfall statistics 1951–2004" and various yearly editions of season and crop reports, published by Directorate of economic and statistics, Government of Andhra Pradesh.

[3] Refer Percival and Walden (2000) for a more detailed exposition of wavelets in time-series analysis.

[4] The admissibility allows the reconstruction of $x(t)$ from the CWT.

[5] The Fourier transform of the wavelet function $\psi(t)$ is $\Psi(\omega) = \int_{-\infty}^{\infty} \psi(t)\, e^{-i\omega t} dt$.

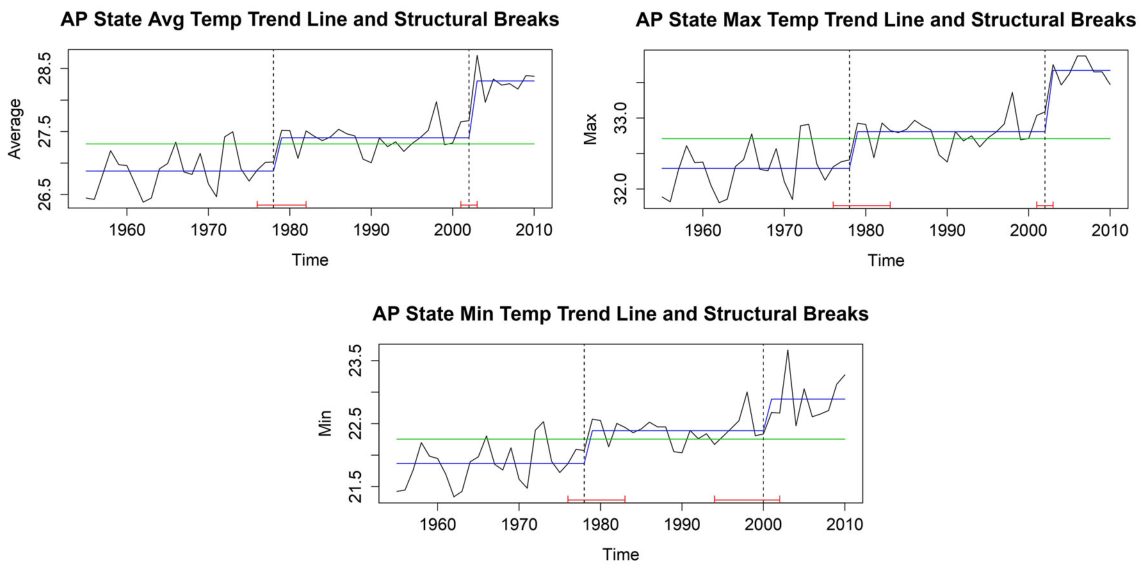

Fig. 1 Temperature dynamics in the undivided state of Andhra Pradesh

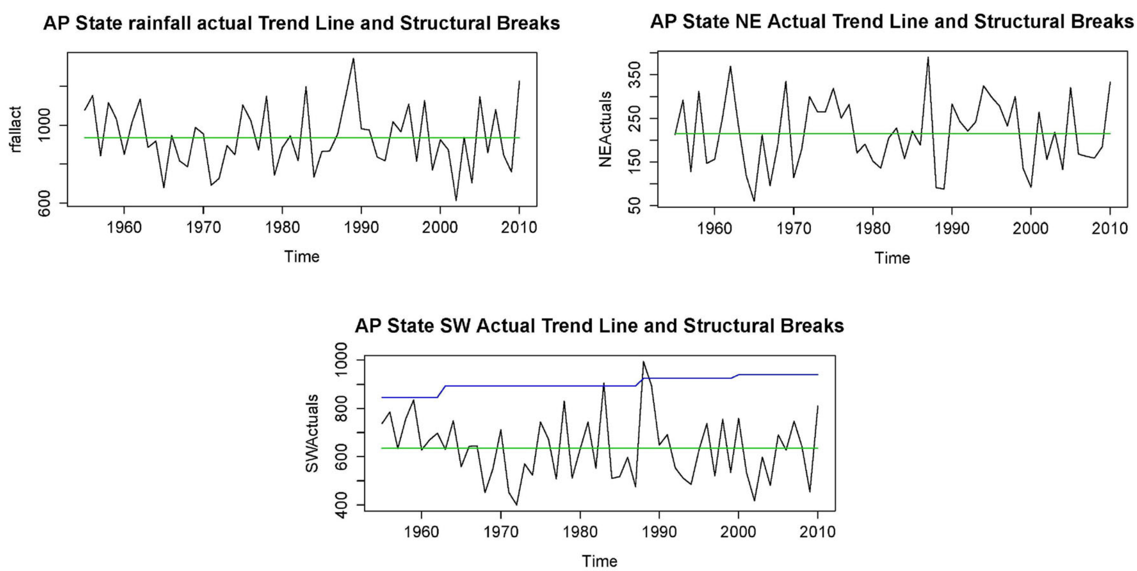

Fig. 2 Rainfall dynamics in the undivided state of Andhra Pradesh

Data on temperature variables is taken from Indian water portal and different volumes of Statistical abstracts, Government of Andhra Pradesh.[6] The erstwhile state of Andhra Pradesh has been bifurcated in 2014 into two new states, Andhra Pradesh and Telangana. Hence our analysis is limited to 2010 due to unavailability of combined state level data of climate and crop variables.

[6] Though the station level data as captured by the IMD (Indian metrological department) is available from as early as 1955, the presence of large gaps across the time, coupled with the absence of stations in many districts during the earlier years has restricted the use of this data set.

4 Empirical results

In this section we discuss the trend and time frequency dynamics of climate and crop yields and the co-movements across time horizons derived from our analysis.

4.1 Crop climate trends in the undivided state of Andhra Pradesh

Figure 1 depict the trend and structural breaks of different temperature parameters for the undivided state of Andhra Pradesh during 1956–2010. The break years have been depicted by the dotted vertical on the *x* axis. All results are

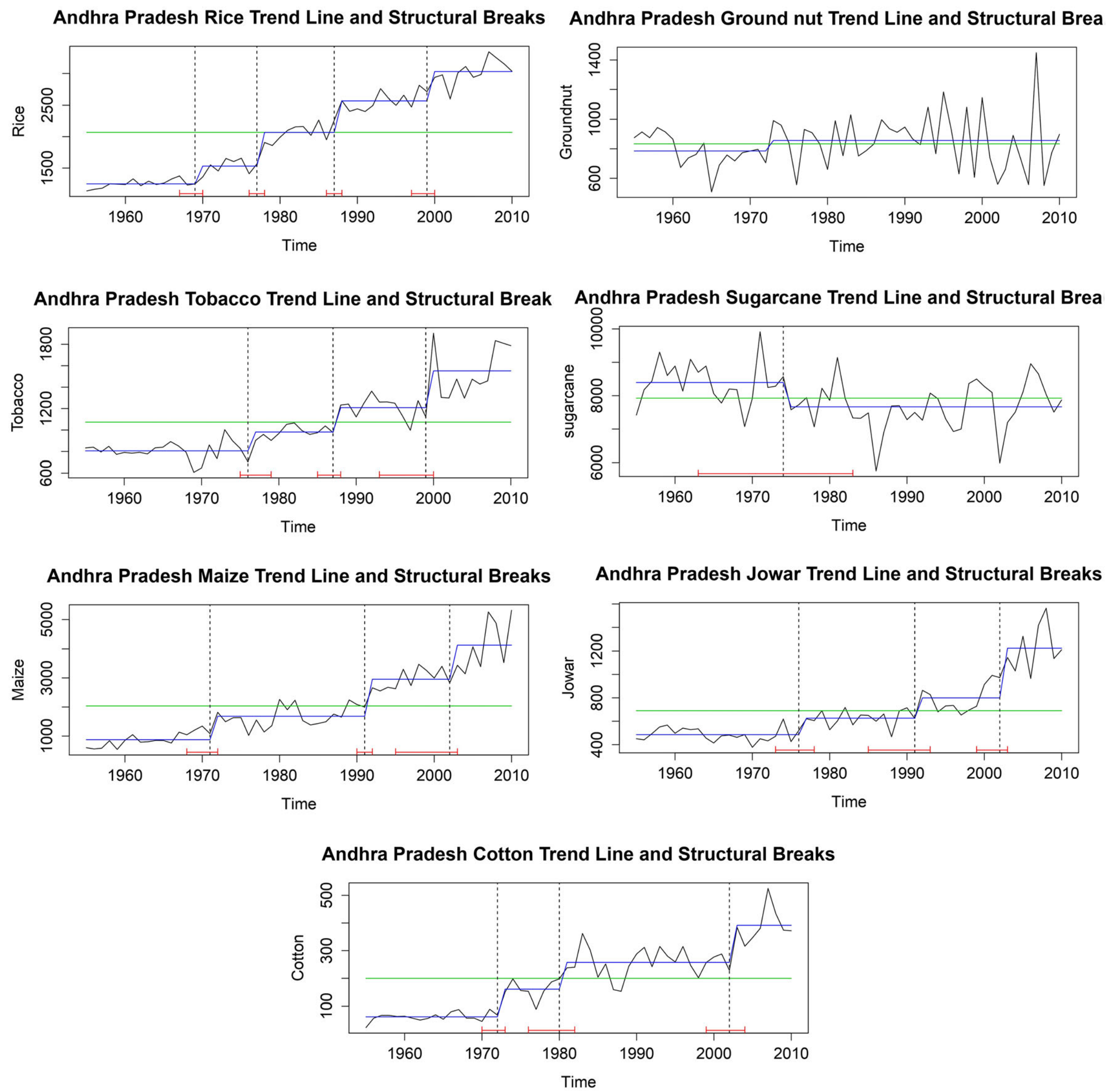

Fig. 3 Yield dynamics of major crops in the undivided state of Andhra Pradesh

at 95% significance level. From the results we observe a steady increase of around 1.0° in annual average, annual maximum and annual minimum temperatures across break points over the study period. All the three temperature variables depict two similar breaks in 1978 and 2002, however annual minimum temperature exhibited a break in 2000. We can observe that the uptick in trend is more visible and pertinent in the later part of the last decade especially around late 1990s to 2000s. This is in line with all India trend that depicts greater warming activity observed in the last 40 years (1971–2010), and particularly attributed to the intense warming in the last decade (1998–2007) (Kothawale et al. 2010).

With reference to rainfall in the state (Fig. 2), we observe that the trend is steady for all the three variables i.e annual average, South-West and North-East rainfall over the study period. As in the case with all India trend (Kumar et al. 1992; Prasad and Kochher 2009), rainfall fluctuations in Andhra Pradesh with no identified break, have been largely random with no systematic change over the study period. However, in line with all India trend (Kumar et al. 1999a,b; Gadgil et al. 2002), actual rainfall depicts oscillating pattern over the years, with regional differences and multi-decadal variations

Yields of major principal crops have recorded positive increase as depicted in Fig. 3. However, yield trends of sugarcane and groundnut show volatility with no significant upward trend. Regarding break points, all crops except sugarcane and groundnut have recorded three or more beak points. While rice exhibited four breaks at 1969, 1977, 1987 and 1999, jowar (1976, 1991, 2002), maize (1971, 1991, 2002), cotton (1972, 1980, 2002) and tobacco (1976,

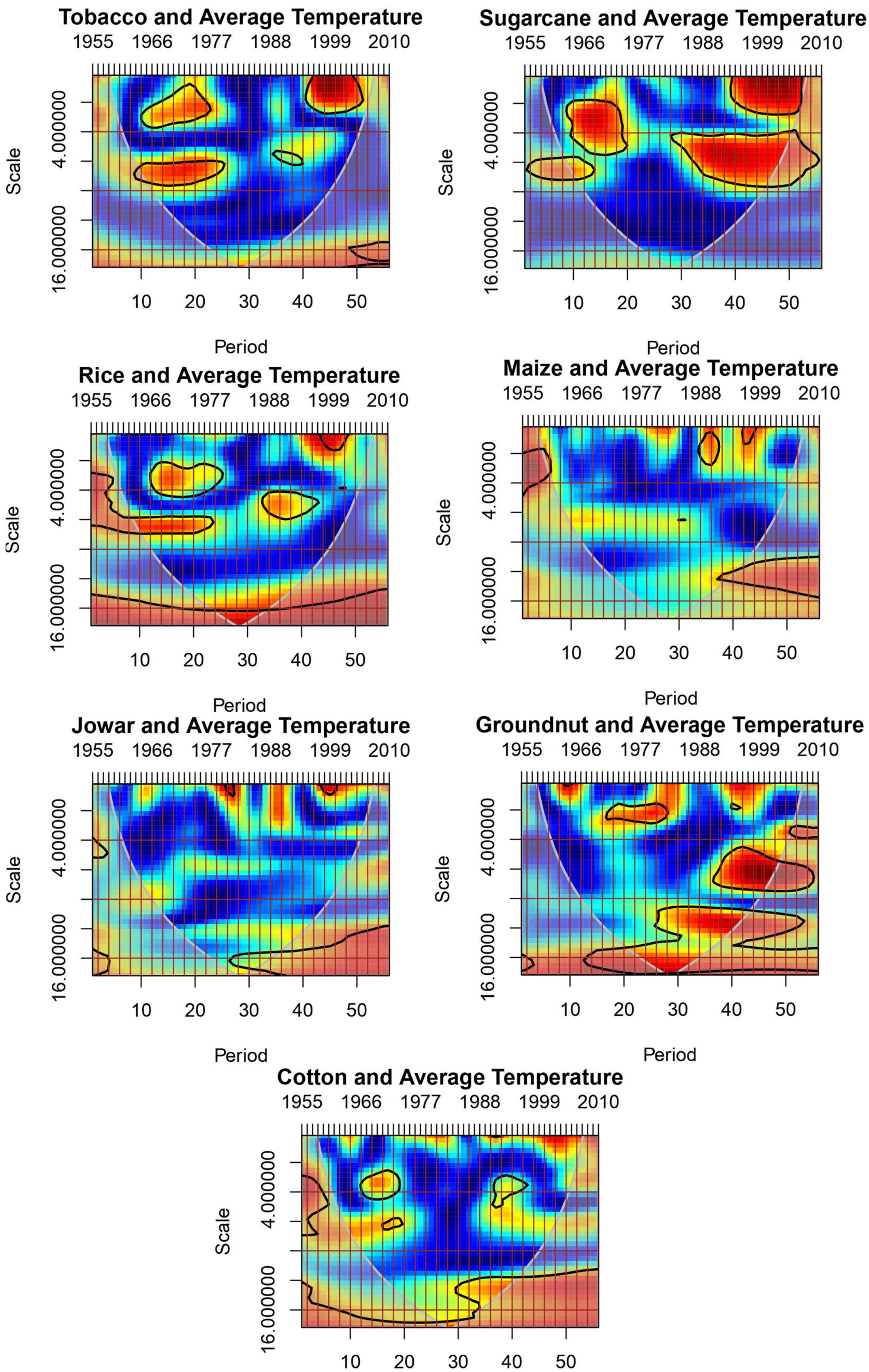

Fig. 4 Coherence of crop yields with temperature

1987, 1999) exhibited three breaks each. For all crops, except jowar and tobacco, the first observed break point is around early part of 1970s, while the last observed break for all the crops is around 1999–2002. We can observe that the last observed break point of temperature is around the same time period as of yields. Even regarding rainfall, the last decade shows an increasing oscillating pattern, implying higher inconsistencies across the years. It must be mentioned here that though yields of major crops are increasing, there is however a deceleration in the yield growth over time (Padakandla 2016). This phenomenon is more visible especially in the last two decades, which coincidentally is the time during which the state has experienced uptick in temperature patterns.

4.2 Wavelet co-movement

Having analyzed the trends in climate and crop yields, we employed continuous wavelet transform method to validate our results and to understand coherence between crop and climate variables across different time horizons. Figure 4 shows the wavelet coherence between temperature and seven crops. It can be seen from the figure that concentration of power or high coherence of average temperature with tobacco, rice, jowar, groundnut and sugarcane, given in red color code, at yearly time horizon manifests around 1995. Overall, high coherence or co-movement between average temperature and the crop yields under study seems to be significant at yearly time horizon and time interval between 1995 and 2000. However, coherence between average temperature and crops changes when the time horizon increases. For example, significant coherence between rice and average temperature can be observed at a time horizon of four years for the time interval 1967–74. The same phenomenon can be observed if we look at the coherence of average temperature with tobacco and sugarcane but not for the other remaining crops under study. This can be attributed to similarity in climatic dependence of rice, sugarcane, and tobacco on crop yield. Furthermore, groundnut and sugarcane seem to exhibit high coherence with average temperature when we consider higher time horizon of six-eight year during the time interval 1990–2000. For these two crops, yield show high co-movement with average temperature during 1990–2000, time interval, but only at much longer time horizon i.e. six-eight-year horizon. No immediate impact can be seen from the analysis, but there seems to be a definite high negative impact on the yield patterns of these two crops over the long run. Therefore, except for yearly time scale, coherence tends to change when the time horizon increases. The results obtained in Fig. 4 is also in consonance with results obtained from structural break analysis which shows observable breaks in temperature and yields around 1995–2000 and in line with decelerating yield growth observed during the same period (Padakandla 2016). Figure 5 reports coherence between rainfall and the seven crops under study. One can observe from the figure that there exists high coherence of actual rainfall with rice, jowar, maize and sugarcane during 1975–80 at yearly time horizon. Similarly, significant coherence of actual rainfall with rice, tobacco, and maize can be observed during 1995–2000 at yearly time horizon. One can observe significant coherence of actual rainfall with rice, maize, and tobacco during 1995–2000 at two to three-year horizon. However, coherence of actual rainfall and the crops under study changes when we look at higher time horizons. For example, the coherence of actual rainfall with cotton, maize, and rice seems to be significant during 1985–1994 at six-year time horizon. Though rainfall pattern does not observe any specific structural change in our analysis, coherence of rainfall with crop yields is in line with the existing literature in the context of India (Parthasarathy and Pant 1985; Parthasarathy et al. 1992; Selvaraju 2003; Kumar et al. 2004).

4.3 Coherence analysis of co-movement across time horizons

The wavelet-based coherence analysis of co-movement between climatic and select crops yields reveal the existence of high coherence of average temperature with crops under study during 1995-2000 at yearly time horizon. However, co-movement among climatic and crop yield tend to vary as we move towards longer time horizon. This is evident when we look at the coherence of average temperature with rice, tobacco, and sugarcane during 1967–74 for four-year time horizon. The coherence further varies, for groundnut and sugarcane, if we look at longer time horizon of six-eight year during the time interval 1990–2000. On the other hand, coherence of rainfall with crops like rice, jowar, maize, and sugarcane is significant during 1975–80 at yearly time horizon. The same is also true for rice, tobacco, and maize during 1995–2000. Similarly, coherence of rainfall with rice, maize, and tobacco is significant during 1995–2000 if we look at the short-run horizon of two-three year. The phenomenon of rising co-movement during long-run time horizons is also evident in the case of rainfall where there exists strong coherence of actual rainfall with cotton, maize, and rice during 1985–1994 at six-year time horizon. The crop-wise climatic coherence for all variables under study is summarized in Table 1.

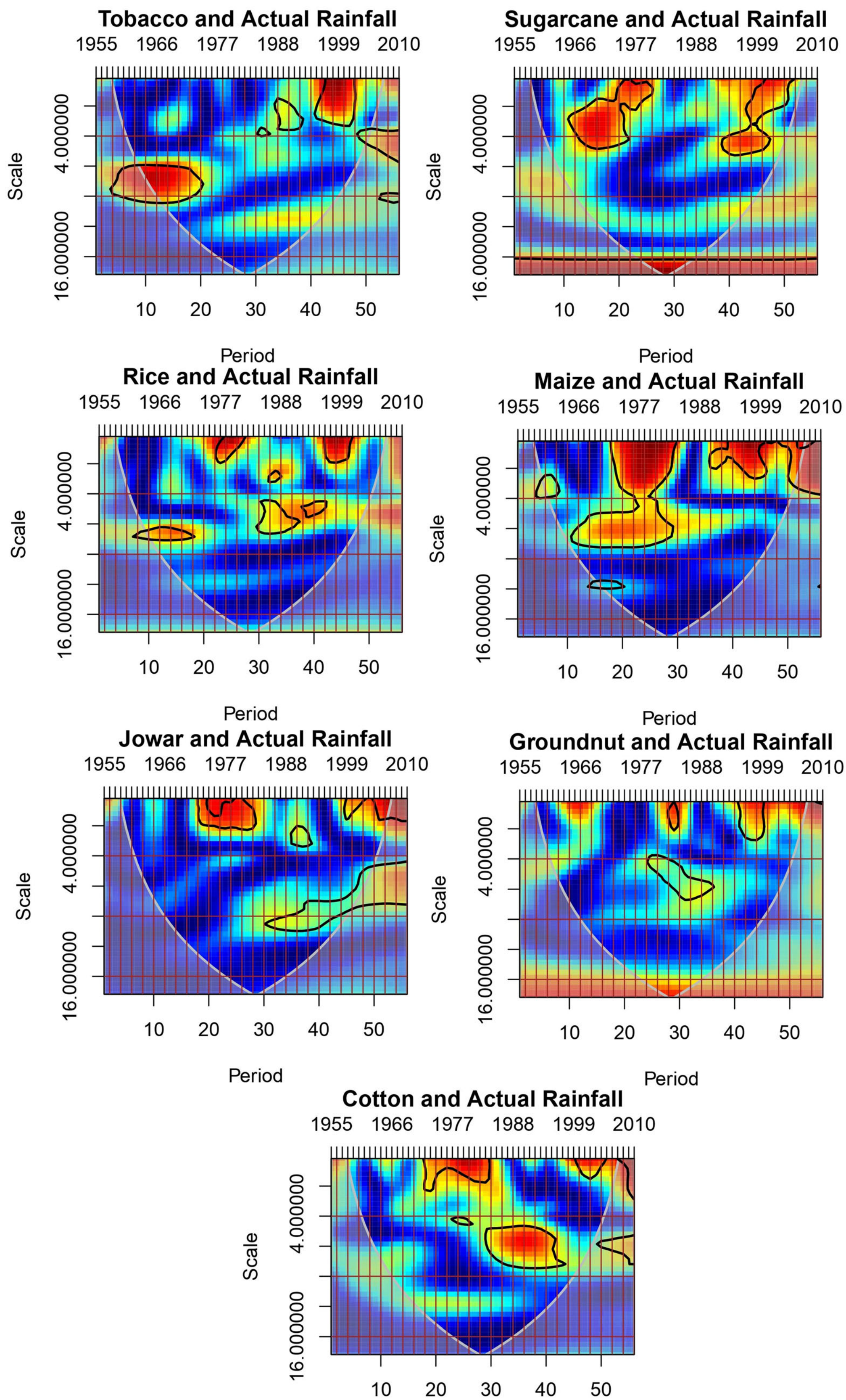

Fig. 5 Wavelet Coherence between crops and rainfall

Table 1 Coherence of climatic variables with crops at varying time-horizon

	Rice	Cotton	Jowar	Groundnut	Maize	Tobacco	Sugarcane
One-year Time Horizon							
Rainfall	High Coherence (around 1975–80) and (around 1995–2000)		High Coherence (around 1975–80)		High Coherence (around 1975–80)	High Coherence (around 1975–80) and (around 1995–2000)	High Coherence (around 1975–80)
Temperature	High Coherence (around 1995–2000)		High Coherence (around 1995–2000)	High Coherence (around 1995–2000)		High Coherence (around 1995–2000)	High Coherence (around 1995–2000)
Two–Three years' Time Horizon							
Rainfall	High Coherence (around 1995–2000)				High Coherence (around 1995–2000)	High Coherence (around 1995–2000)	
Temperature							
Four-year Time Horizon							
Rainfall							
Temperature	High Coherence (around 1967–74)					High Coherence (around 1967–74)	High Coherence (around 1967–74)
Six-Eight years' Time Horizon							
Rainfall	High Coherence (around 1985–94)	High Coherence (around 1985–94)			High Coherence (around 1985–94)		
Temperature				High Coherence (around 1990–2000)			High Coherence (around 1990–2000)

5 Conclusions

Results show that observed variables exhibit multiple structural break points implying significant changes in climatic and crop yield patterns over the years in the undivided state of Andhra Pradesh. Results also depict a convergence of break points for most of crop and climate variables. Wavelet based coherence analysis that map the time-horizon specific dynamics of climate and crops with time periods exhibited significant co-movement between climatic and crop variables. This mapping, however, cannot be explored with traditional time-series methods. The framework of wavelets-based time-frequency analysis employed in this study captures climate and crop dynamics at heterogeneous time horizons. This allows one to study the impact of climate and crop yields at both short and longer time-horizons. Furthermore, we show that climate-induced crop variations change with varying time-horizons even at the sub-national level which has not been captured in existing literature.

Climate adaption and mitigation strategies across the world and more so in developing countries are predominately static in nature and do not incorporate changing time-horizons into consideration. Incorporating the effects of climatic changes in climate-induced crop yields at varying timescale will allow to formulate dynamic adaptation strategies and may help gauge the impact of adverse future climatic events on crop yield. The substantial variation in climate-induced crop yields across the geography under study and across timescales as unraveled by our empirical analysis provides an exciting perspective for researchers engaged in forecasting climate-induced crop variabilities. The time varying impact of climate on crop yields as evidenced in our study helps policy makers and crop scientists to design time specific and locally viable adaption and mitigation policies to tackle the impact of climate on crops and livelihoods. The information, data, and maps provided can serve as an assessment guide for planners, managers, and policy and decision makers to prioritize agricultural resilience efforts and resource allocation or re-allocation in the regions that exhibit risk from climate variability.

The limitation of the study stems from the fact that our dataset consists of only fifty-five yearly time-series observations which can limit the robustness of the model. Similarly, the absence of phase analysis which helps in analyzing the lead-lag behavior between climatic and crop variables is outside the purview of our analysis and can be potential scope of future study along similar lines.

Author's contribution SR Padakandla: Conceptualization of the idea, data collection and formulation and preparing of manuscript; A Bhandari: Analysis of Wavelet co-movements; AA Atluri: Structural break analysis.

Funding There is no funding for this research.

Data availability The data has been uploaded.

Declarations

Conflict of interest There is no financial or personal relationships, or conflict of interest that could be perceived as potential source of bias.

Consent to Participate We here-by provide our full consent to participate in the process of the journal.

Consent to Publish We here-by provide our full consent to publish our article in the journal.

Ethical approval This article does not contain any studies with human or animal participants performed by any of the authors.

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