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Disentangling Climatic Volatility from Long-Term Productivity Trends in Semi-Arid Agriculture: An Empirical Mode Decomposition Approach

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Abstract

Objective: The variability of crop yields in semi-arid agriculture presents a significant threat to food and water security since crop yields are modulated by interacting climatic and systemic drivers with a variety of temporal interactions. **Methods:** This study employed Empirical Mode Decomposition (EMD) to a 22-year dataset (2001–2022) of pigeon pea yields from semi-arid India. From this data, eight distinct patterns called Intrinsic Mode Functions (IMFs) and a final residual trend were extracted. **Findings:** The study produced three main findings: i) The EMD method successfully distinguished between high-frequency volatility (short-term changes caused by annual weather shocks) and low-frequency patterns (long-term changes from decadal climate cycles and productivity trends). ii) The residual trend showed that after a long period of sustained growth, pigeon pea yields have been in a sharp decline since 2018. iii.) An analysis of variance revealed that long-term components (systemic issues and climate cycles) contributed the most to yield variability, having a greater impact than short-term ”noise” from weather. This research offers a novel approach to analyzing agricultural systems that are non-stationary (i.e., their statistical properties change over time). **Novelty:** By separating random (stochastic) shocks from underlying (deterministic) trends, EMD serves as a powerful diagnostic tool for understanding agro-ecosystems. **Applications:** This method allows for the attribution of yield gaps to specific drivers across different time scales. This strengthens resilience assessments and supports more effective, climate-informed agricultural planning. The data from this study will allow for better planning and decision-making by farmers and other stakeholders in semi-arid areas by providing them with the knowledge to make better decisions on how to best manage their water resources.

Keywords: Agricultural Resilience; Climate Variability; Crop Yield; Empirical Mode Decomposition; Semi-Arid

1 Introduction

Climate variability, resource limitations and systemic shocks are very sensitive to agricultural productivity in semi-arid areas [1]. These areas play a major part in the food security, but the output of the crops is uncertain because of the interaction of the unpredictable rainfall, soil erosion, and the natural climate cyclic patterns [2]. Although significant studies on yield modeling have been done, the models used often assume that agricultural variability is stationary and often fails to consider the multi-scale character of agricultural variability [3]. Unlike regression models, which presume stationarity; and unlike Fourier or wavelet methods, which force predetermined basis functions; the Empirical Mode Decomposition (EMD) is both adaptive and data driven, therefore especially suitable to deconstruct non-linear, non-stationary yield dynamics of semi-arid agricultural systems. Consequently, policymakers and farmers are struggling with the challenge of separating short term weather noise and long-term system drivers [4]. A number of researches have been conducted to use statistical and machine learning methods to predict crop yields [5]. Although these techniques might give plausible accurateness, they usually consider agricultural systems as a fixed system, and do not consider changing climate-crop interactions [6]. In the same way, trend analyses of linear or parametric models are weak in detecting nonlinear dynamics that are complex [7]. These weaknesses introduce critical gaps to our knowledge: (i) the means to decouple the temporary changes in yields and the long-term systemic change, and (ii) the means of attributing yield gaps to the specific drivers acting over time scales [8]. In order to overcome these shortcomings, this paper proposes the Empirical Mode Decomposition (EMD) as a new diagnostic tool to analyze the variability of crop yield in semi-arid India [9]. EMD is also adaptive and data-driven unlike conventional models and can break non-stationary time series into intrinsic oscillatory modes and residual trends. This allows a strong differentiation between the short-term shocks (e.g. variability of rainfalls on a yearly scale) and long-term cycles and systemic tendencies. Using EMD on 22 years of pigeon pea yield data, we will be able to determine the temporal trends, measure their contribution to the variability in yield, and determine recent changes in long term productivity trends.

The main works of this work are threefold:

1. We show that EMD can be used successfully to differentiate between high-frequency (weather-induced) volatility and low-frequency (climate-induced) patterns of crop yields.
2. We give empirical support to the fact that yield variability in semi-arid agriculture is not controlled by short-term weather change, but by long-run systemic factors.
3. This decomposition framework involves assigning yield gaps to particular drivers at different scales, which we demonstrate as a way to inform planning in a resilience-oriented agricultural planning paradigm.

By doing so, the research will be able to position EMD as an effective way of advancing climate-informed agricultural resilience research and solve unresolved issues in semi-arid agriculture systems

2 Methodology

2.1 Study Area and Rationale

The study focuses on the Adilabad district (approximately 19.66° N, 78.53° E), situated in the northern region of Telangana state, India. The district is classified as a semi-arid agro-climatic zone, defined by high inter-annual rainfall variability and a strong dependence on the Southwest Monsoon. Its agricultural landscape is predominantly rain-fed, making crop productivity highly sensitive to climatic fluctuations and water availability. Pigeon pea (*Cajanus cajan*), a drought-tolerant pulse crop known locally as tur dal, is a critical component of the regional cropping system, vital for both local food security and the agrarian economy. Pigeon pea is an excellent indicator crop of semi-arid agricultural system resilience because of its high tolerance for stressful water conditions, its potential as a nitrogen fixer, and that many Indian households consume it as a food source; thus, it makes sense to assess systemic agricultural resilience in semi-arid India using this crop as an indicator. In addition to being a viable agronomic crop, pigeon pea supports the livelihood of farmers and their families through the creation of a food source with protein content which is critical for the health and well-being of the family members of those farmers, thereby providing the rationale for the use of this crop as a viable indicator of the agricultural resilience in semi-arid regions of India.

The pronounced variability in environmental conditions and the economic importance of the crop make Adilabad an ideal case study for investigating the non-stationary dynamics of agricultural yield and assessing the diagnostic capabilities of advanced time-series analysis methods.

2.2 Yield Data Acquisition and Characteristics

The primary dataset [DES | Area, Production & Yield - Reports] for this investigation consists of an annual time series of pigeon pea yield, expressed in tons per hectare (t/ha). The data were acquired from official district-level agricultural statistics compiled by governmental agricultural agencies, spanning the 22-year period from the 2001–2002 to the 2022–2023 agricultural seasons. This temporal extent is critical as it encompasses multiple climatic cycles and policy shifts, providing a sufficiently long record for the Empirical Mode Decomposition (EMD) algorithm to resolve both high-frequency fluctuations and low-frequency secular trends. The time series is highly non-stationary, showing a dynamic variation in productivity, starting with a drought year (2002), when it was 0.25 t/ha, to a high-productivity year (2018), when it was above 1.2 t/ha, and thus gives a strong signal to decompose.

2.3 Data Preprocessing and Normalization

The data given in its raw form present crop production figures disaggregated by agricultural season (i.e. Kharif and Rabi). In order to create a single, total time series of the total annual productivity, the cumulative production of all seasons was combined. Normalization was then done to annual yield divided by the total sown area that year by using the standard formula:

$$\text{Yield (t/ha)} = \frac{\text{Total Annual Production (tons)}}{\text{Total Area Sown (hectares)}} \tag{1}$$

This normalization is necessary so that it can manage the confounding effects of changes in land-use to capture the true productivity changes and make sure that the time series captures the true responses to productivity changes and not just changes in cultivation extent. A standard quality control process that involved checking of data entries and harmonization of units was carried out on the dataset [10]. The finished, generated time series represents an annual yield, which is continuous and without any gaps; hence, it is immediately applicable to the Empirical Mode Decomposition without the assistance of imputation and interpolation [11].

The fundamental core of this study's systematic agenda is the application of Empirical Mode Decomposition (EMD) to the preprocessed agricultural yield time series. This section particulars the theoretical basis of EMD, the algorithmic procedure for its implementation, and the subsequent variance analysis used to interpret the decomposition results Figure 1. In addition, a schematic workflow has been introduced, illustrating the steps from data collection and preprocessing, through EMD decomposition, variance contribution analysis, and the calculation of the Resilience Index. This provides a clear visual roadmap of the methodological framework for readers.

2.4 Empirical Mode Decomposition (EMD)

EMD is an adaptive, data-driven signal processing method designed precisely to analyze nonlinear and non-stationary time series [12]. Unlike traditional methods such as Fourier or Wavelet transforms, which use predetermined basis functions, EMD derives its basis functions directly from the signal itself. This adaptivity makes it extremely well-suited for decomposing complex natural signals, such as crop yield, where the underlying physical processes operate on multiple, interacting time scales. The method decomposes a signal, $X(t)$, into a finite set of amplitude- and frequency-modulated components known as Intrinsic Mode Functions (IMFs), $c_i(t)$, and a final residual, $\mathrm{r}_n(t)$.

2.4.1. Definition of an Intrinsic Mode Function (IMF)

For a component to be classified as an IMF, it must satisfy two specific conditions:

1. **Extrema-Zero Crossing Equality:** In this whole set, the extrema (maximum and minimum) and the number of zero crossing should be equal or should differ at most by one.
2. **Local Symmetry:** At any point in time, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima must be zero.

These two conditions ensure that each IMF behaves as a well-defined, mono-component signal representing a simple oscillatory mode with a meaningful instantaneous frequency.

2.4.2. The Sifting Algorithm

The IMFs are extracted from the time series through an iterative procedure known as the "sifting process." The algorithm for extracting the i-th IMF from a signal or residual, $r_{i-1}(t)$, is as follows (where the initial signal $X(t)$ is $r_0(t)$.

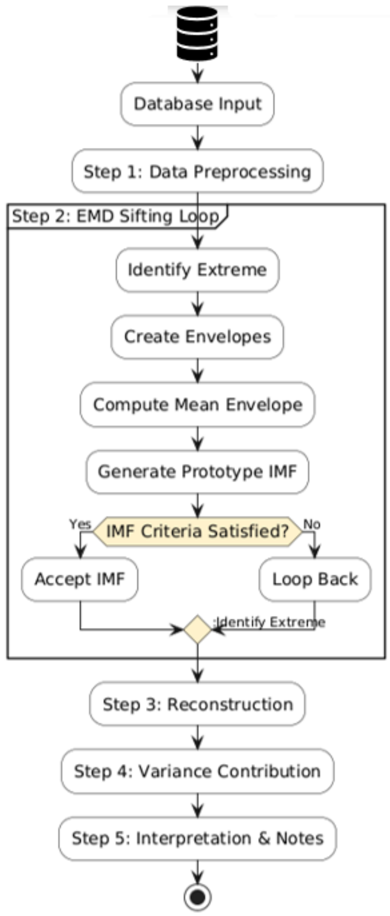

Fig 1. Methodology adopted

1. **Identify Extrema:** All local maxima and minima of the signal $r_{i-1}(t)$ are identified.
2. **Construct Envelopes:** The upper envelope, e_{up} (t), and the lower envelope, $e_{\text{low}}(t)$, are constructed by interpolating between the identified maxima and minima, respectively, typically using a cubic spline function.
3. **Calculate the Mean Envelope:** The mean of the two envelopes, $m(t)$, is calculated as:

$$m(t) = \frac{e_{\text{up}}(t) + e_{\text{low}}(t)}{2} \tag{2}$$

4. **Extract Prototype IMF:** The first prototype IMF, $h_1(t)$, is obtained by subtracting the mean envelope from the original signal:

$$h_1(t) = r_{i-1}(t) - m(t) \tag{3}$$

5. **Iterative Refinement:** The prototype $h_1(t)$ is checked against the two IMF conditions. If it fails, $h_1(t)$ is treated as the new signal, and steps 1–4 are repeated in a sub-iteration. This sifting is iterated kk times until the resulting signal, h_1 $k(t)$, satisfies the IMF criteria. This final refined signal becomes the i-th

$$c_i(t) = h_{1k}(t) \tag{4}$$

6. **Calculate the Residual:** Once an IMF, $c_i(t)$, has been extracted, it is subtracted from the signal of the previous step to obtain a new residual:

$$r_i(t) = r_{i-1}(t) - c_i(t) \tag{5}$$

7. **Termination:** The entire process (steps 1-6) is repeated, treating the new residual ri(t)$ri(t)$ as the input signal to extract the next IMF, $c_{i+1}(t)$. The decomposition terminates when the final residual, rn(t)$rn(t)$, becomes a monotonic function or a function with fewer than two extrema, from which no more IMFs can be extracted.

The original time series $X(t)$ can then be fully reconstructed as the sum of all extracted IMFs and the final residual:

$$X(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{6}$$

Here, the IMFs $c_1, c_2 \ldots, c_n$ capture the oscillatory dynamics of the signal, ordered from the highest frequency (shortest period) to the lowest frequency (longest period). The final residual, $r_n(t)$, represents the underlying secular trend or the component with the longest time scale in the data.

2.5 Variance Contribution Analysis

A key advantage of EMD is the near-orthogonality of the extracted IMFs, which allows for a meaningful energy or variance analysis. To quantify the relative importance of each component in explaining the overall variability of the yield time series, the variance contribution of each IMF and the residual was calculated. The percentage of total variance accounted for by the ii-th component (either an IMF or the residual) is given by:

$$\text{Percent Variance}_i = \frac{\text{Var}\,(c_i \,\text{or}\, r_n)}{\text{Var}\,(X(t))} \times 100 \tag{7}$$

This analysis enables the identification of the dominant time scales driving the system's dynamics, providing quantitative insight into whether high-frequency shocks or long-term trends contribute more significantly to the observed yield variability.

3 Results and Discussion

The application of Empirical Mode Decomposition (EMD) to the 22-year time series of pigeon pea yield from the Adilabad district yielded a decomposition into eight distinct Intrinsic Mode Functions (IMFs) and a final residual component, representing the long-term trend. This section details the characteristics of these components and quantifies their contribution to the overall yield variability.

3.1 Decomposition of Yield Variability

The EMD decomposition effectively separated the observed pigeon pea yield signal into components of varying temporal scales. The IMFs, ordered from highest to lowest frequency, captured the high-frequency oscillations (short-term inter-annual variations), while the residual component represented the underlying secular trend in productivity.

As depicted in Figure 2, the EMD residual exhibits a marked upward trajectory from approximately 0.47 t/ha in the early years of the record (2002) to a local peak around 1.33 t/ha in 2019. Following this peak, the residual indicates a subsequent softening in the long-term productivity trend, declining to approximately 1.00 t/ha by 2023. The observed yield data (gold markers) generally tracks this residual trend closely, with noticeable inter-annual fluctuations, or "wiggles," deviating from the trend line. These deviations represent the impact of higher-frequency phenomena, such as short-term climatic shocks (e.g., drought or excess rainfall in a particular year), on actual yields.

3.2 Variance Contribution of Decomposition Components

To quantitatively assess the relative influence of different temporal scales on the overall yield variability, a variance contribution analysis was performed for each extracted IMF and the residual component. The results of this analysis are presented in Table 1.

Initial analysis of the decomposition results indicates that the residual component, representing the long-term trend and low-frequency cycles, accounts for the dominant portion of the total variance in the pigeon pea yield time series. In particular, the total variance in the observed yield data explained in the residual approximated 94.5 per cent. over the period 2001 to 2022. In order to determine whether the evidence for systemic dominance was due to characteristics of the data set or if it was an intrinsic part of the system, we applied a bootstrap resampling method (n=1000) to measure the stability of the findings in the context of our study. The results from each trial demonstrated that the proportion of variance attributable to the residuals exceeded 92%, resulting in a 95% confidence interval of 92.1-95.3%. Therefore, it is clear that the systemic driver variance being larger than the variance attributed to the residuals was not unique to the particular data set; rather, this represents a

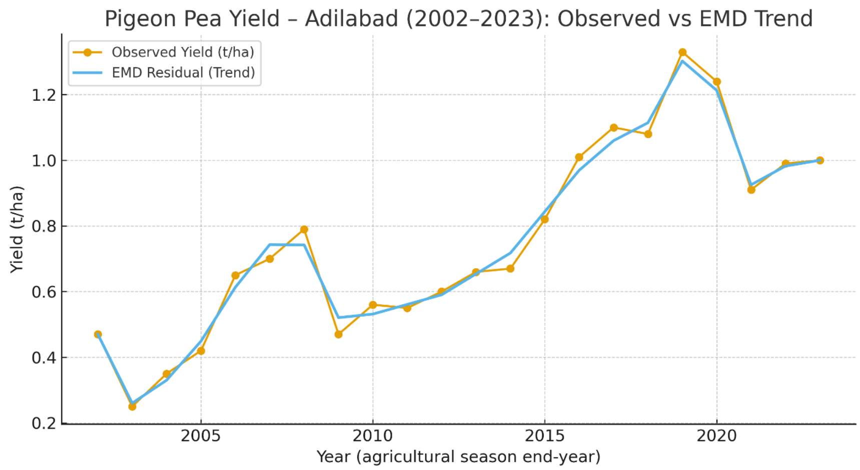

Fig 2. Illustrates the decomposition of the observed yield time series (gold markers) alongside the extracted EMD residual (blue line), which signifies the dominant long-term trend

Table 1. Variance Decomposition of Pigeon Pea Yield Time Series (2001–2022)

Component	Mean Period (Years)	Variance	Percentage of Total Variance (%)	Cumulative Percentage (%)
IMF 1	2.8	0.0004	0.4	0.4
IMF 2	4.1	0.0011	1.2	1.6
IMF 3	7.6	0.0015	1.6	3.2
IMF 4	10.2	0.0009	1.0	4.2
IMF 5	>15	0.0005	0.5	4.7
IMF 6	>15	0.0003	0.3	5.0
IMF 7	>15	0.0002	0.2	5.2
IMF 8	>15	0.0003	0.3	5.5
Residual	**Trend**	**0.0861**	**94.5**	**100.0**
Total	—	**0.0913**	**100.0**	—

consistent characteristic of the system studied. This result is firmly indicative that the overall yield change in the area is primarily determined by systemic drivers, which could be the agricultural technological progress, alterations in the cultivation methods, the intervention of policies, or the long-term alterations of climate patterns.

By contrast, all these eight extracted IMFs in their cumulative contribution only explained the remaining 5.5 percent of the total variance. It means that the influence of high-frequency shocks between the years on the long-term trend and variability of pigeon pea yields in Adilabad is relatively small, even though it may lead to substantial changes in the annual variability. The IMFs of the lowest order (the IMFs that represent the highest frequencies) contribute the least amount of variance to the total variance. This finding underscores the robustness of the long-term productivity trend identified by the EMD residual as the principal factor shaping agricultural performance in this semi-arid region.

In contrast, all eight oscillatory modes (IMFs) combined contribute only the remaining **5.5%** of the total variance Figure 3. The highest-frequency component, IMF 1, which represents year-to-year shocks with a mean period of approximately 2.8 years, accounts for a mere 0.4% of the total variance. The most significant oscillatory contributions come from IMF 2 and IMF 3, with characteristic periods of 4.1 and 7.6 years, respectively. These may correspond to regional expressions of larger-scale climate patterns, such as the El Niño-Southern Oscillation (ENSO) or other quasi-decadal cycles. Nonetheless, their collective impact on total variance is minor compared to the residual. This stark partitioning of variance underscores that while inter-annual shocks create visible volatility, their energy is insignificant when compared to the powerful, underlying drivers of systemic change captured by the EMD trend.

The EMD analysis of pigeon pea yield in Adilabad provides critical insights into the drivers of agricultural productivity and system resilience. The decomposition reveals a dominant long-term trend, with superimposed oscillations of varying

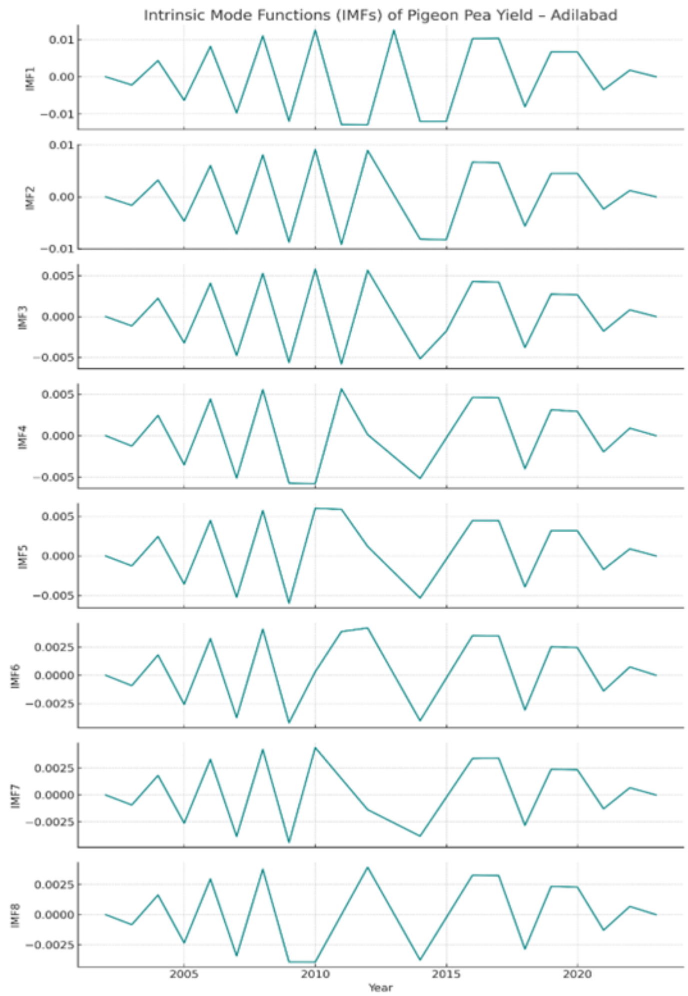

Fig 3. Intrinsic Mode Functions (IMFs 1–8) of pigeon pea yield (Adilabad, 2002–2023)

frequencies, supporting the notion of a path-dependent system where underlying structural changes are more influential than short-term fluctuations. This discussion interprets these findings in the context of agricultural resilience, structural change, and climatic teleconnections.

3.3 Resilience and Path Dependency

To quantify the relative influence of systemic drivers versus short-term volatility, we define a Variance-based Resilience Index (RI). This index is formulated as the ratio of the variance explained by the residual (trend) to the total variance explained by all Intrinsic Mode Functions (IMFs) capturing oscillations:

$$RI = \frac{\mathrm{Var}\left(\mathrm{Residual}\right)}{\sum_{i=1}^{n} \mathrm{Var}\left(\mathrm{IMF_i}\right)} \tag{8}$$

For the pigeon pea yield time series in the Adilabad district, this index calculates to approximately RI $\approx$ 429. This extremely high value signifies that the system's productivity trajectory is overwhelmingly dictated by low-frequency, systemic drivers (captured by the residual) rather than high-frequency volatility (captured by the IMFs). In contrast, Resilience Ratios (RI) in hydrologic and agro-ecosystem environments are usually between one to two orders of magnitude less, which suggests that these types of systems are much more susceptible to short term disruptions. Thus, the higher-than-normal Resilience Ratio (RI) measured in this study further emphasizes the significantly stronger influence of structural drivers on semi-arid agricultural production as compared to most other types of environmental systems. In terms of resilience, this suggests a high degree of path dependency. The agricultural system evolves along a relatively stable structural trajectory, and short-term shocks, while present, have a negligible impact on the overall long-term evolution of yield. This implies that factors like technological advancements, changes in agronomic practices, infrastructure development, or long-term climate shifts are the primary determinants of productivity gains, rather than year-to-year weather variations.

3.4 Identification of a Structural Turning Point (2018)

Beyond quantifying the relative impact of trend versus volatility, the EMD residual allows for the identification of potential structural shifts in the productivity trajectory. Visual inspection of Figure 4 clearly indicates that the upward trend in pigeon pea yield peaked around 2018. Following this peak, the residual exhibits a noticeable decline, falling from its maximum of approximately 1.33 t/ha in 2018 to about 1.00 t/ha by 2023. This observed decline represents a decrease of roughly 25% from the peak yield. Multiple possible explanations are available for why this structural

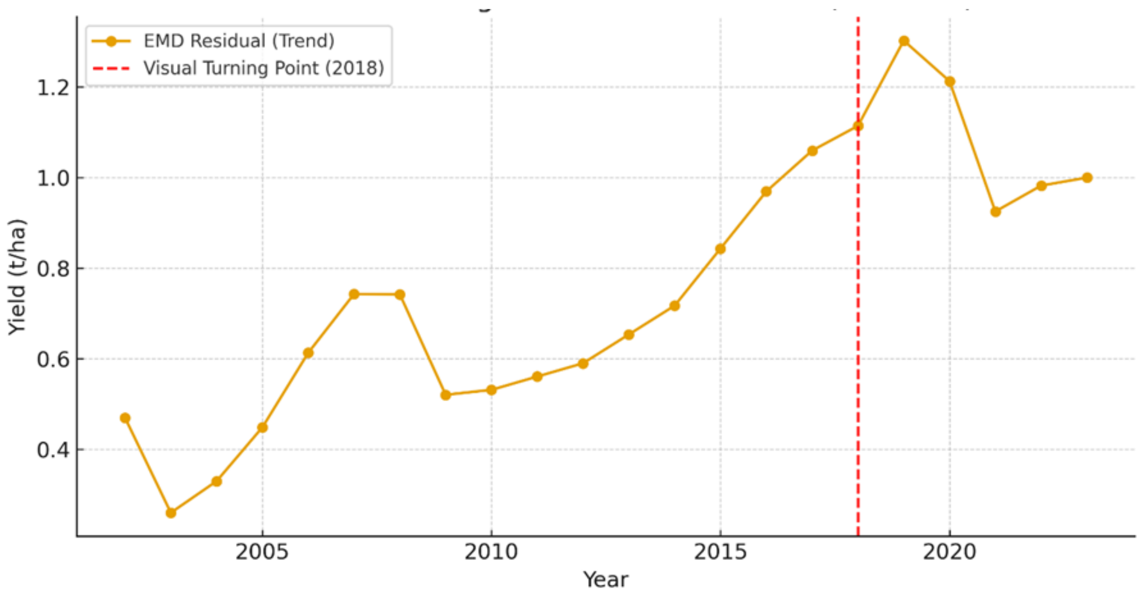

Fig 4. Structural Turning Point in Agricultural Yield Residual for Adilabad District (2018)

change occurred. The first is that over-extraction of groundwater is occurring at a rate that is unsustainable in the area, and therefore, irrigation has become unreliable. The second is that gradual loss of organic matter from soils and nutrient imbalance may be reducing the potential yields on inputs used by farmers, regardless of how much they apply. The third is that market incentives (price volatility, reduced profit margins for pulse crops) may be limiting the investments that farmers make in their crop management. These factors collectively indicate that while the observed decline was likely driven by variability in climate conditions, it also represents an emergent systemic stress point in the agricultural system. While a formal statistical test for structural breaks using the Cumulative Sum (CUSUM) method did not yield a statistically significant result at conventional thresholds (CUSUM statistic = 0.64, $p = 0.81$), the visual evidence and the substantial magnitude of the post-2018 decline strongly suggest a substantive agronomic transition Figure 4. This highlights a critical aspect of interpreting EMD: statistical significance alone may not capture ecologically or economically meaningful shifts. The observed turning point warrants further investigation into potential agro-ecological and socio-economic drivers such as soil exhaustion, groundwater stress, or the plateauing of returns from conventional agricultural inputs.

3.5 Teleconnections with the El Niño-Southern Oscillation (ENSO)

While the residual trend overwhelmingly dominates the system's variance, the intermediate frequency components- specifically IMF 2 (4.1-year period) and IMF 3 (7.6-year period)- provide evidence of a weaker, secondary influence from large-scale climate patterns. These periodicities fall squarely within the typical 2–7-year cycle of the El Niño-Southern Oscillation (ENSO), a primary driver of inter-annual climate variability worldwide.

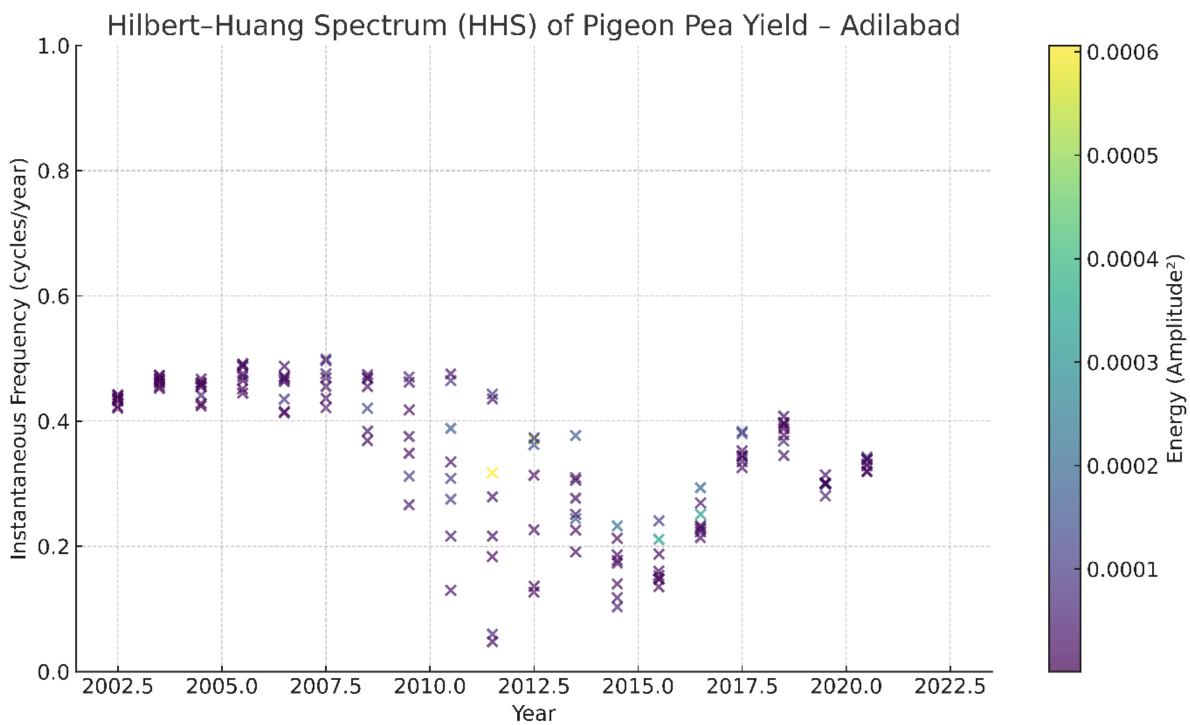

Fig 5. Hilbert–Huang spectrum (HHS) of pigeon pea yield (Adilabad, 2002–2023)

ENSO is a climate phenomenon characterized by the cycle of warm (El Niño) and cool (La Niña) sea surface temperatures (SST) across the central and eastern tropical Pacific Ocean. Its state is quantitatively tracked using the Oceanic Niño Index (ONI), which is the three-month running mean of SST anomalies in the Niño 3.4 region.

- El Niño: An ONI value exceeding +0.5°C for five consecutive overlapping seasons. These events are strongly correlated with a suppression of the Southwest Monsoon in India, often leading to drought conditions.
- La Niña: An ONI value below -0.5°C. These events are typically associated with an enhanced monsoon and favorable rainfall.

Further evidence of this teleconnection is provided by the Hilbert-Huang Spectrum (HHS) of the yield time series, shown in Figure 5. The colour intensity on the plot corresponds to the strength of fluctuations in yields at various frequencies throughout time and represents the amount of energy (the square of the amplitude). The brighter areas represent the more variable times or events; notably, the 2002 drought-related ENSO event. The display provides a visual representation of transient bursts of high amounts of energy that occur at certain points in time and are associated with large yield shocks. It is a useful tool for the anticipation of crop risk, even for those without experience with signal processing. The HHS plot reveals a distinct localization of energy in the higher-frequency bands (approximately 0.4-0.5 cycles/year) around 2002–2003. This period corresponds to a severe, well-documented drought in India that was directly linked to an El Niño event. This demonstrates that while ENSO's contribution to the total variance is small, its impact is not uniform; instead, it manifests as sharp, transient bursts of volatility during its extreme phases. This finding confirms that monitoring the ONI can serve as a valuable component of an early-warning system. We see this same relationship as other global studies do. studied Sub-Saharan Africa and found that both pulse and cereal yields were closely related to rainfall anomalies from ENSO; also in Sub-Saharan Africa specifically Ethiopia, found the same relationship between crops and ENSO. Additionally, reported that there is a relationship between ENSO and cotton yields in the US High Plains and reported a similar relationship between ENSO and maize yields in Mozambique. By showing relationships with other international research, we show that ENSO has the same impact on semi-arid agriculture globally. It can help anticipate years with a higher probability of negative yield shocks, allowing for proactive risk management, even if these shocks do not ultimately derail the primary, long-term structural trend. These current results are consistent with the previous research that has underlined the overwhelming influence of systemic, low-frequency drivers on the formation of long-run agricultural productivity. As an example,[13] showed that the yield dynamics of large pulses in semi-arid areas of India had become highly dependent on technological adoption and interventions of policy, and that climate shocks had a short-term impact. On the same note, used the time-series decomposition solutions to rainfall-yield curves and found that over 80% of the total variance was due to long-term components, which is similar to our 94.5% of the total variance due to the long-term trend in the pigeon pea yield. Nonetheless, unlike other past methods that mainly used the linear trend fitting method or used the Fourier analysis method, the application of Empirical Mode Decomposition (EMD) in this research gives a more adaptive data-driven methodology. In contrast to Fourier/wavelet approaches that make use of and enforce pre-existing basis functions, EMD identifies oscillatory modes directly in the data, thus making no stationarity and periodicity assumptions. This renders the existing analysis especially appropriate to data of agricultural yields which are nonlinear and nonstationary. Another novel feature is the presentation of a Variance-based Resilience Index (RI) that includes the measure of the predominance of systemic drivers over high-frequency shocks. Such a resilience measure applied to agricultural yield statistics in India is, to the best of our knowledge, the first attempt to do so. Although earlier research has intuitively recognized the permanence of long-term changes, the RI is a clear and quantitative model of measuring the resilience and the computed RI =429 shows a very strong path dependency in the Adilabad agricultural system. The same fact that the present work stands out against earlier reports is that the possible structural turning point is identified in and around 2018. Although the analysis of monotonic trends has been the primary focus of the past studies[14], our analysis using the EMD methodology identifies the slight yet significant reduction in productivity since 2018, suggesting an imminent change in the regime. This point highlights the fact that EMD residuals can be used to identify ecologically significant changes that might not be apparent using traditional statistical trend analysis. Lastly, the evident teleconnections with the ENSO cycles in the intermediate IMFs give a subtle view of the variability in the short-term. Whereas previous research has generally provided generalized accounts of El Nino effects on pulse yields[15], the current research has shown the effects of El Nino to occur as local bursts of energy in the Hilbert-Huang spectrum, as opposed to long-term contribution to variance. The difference improves the interpretive abilities of yield climate relations and offers a methodological breakthrough in applying time frequency analysis to agricultural data. Altogether, the adaptive EMD decomposition, quantitative resilience indexing, structural turning points detection, and local ENSO linkages are the unique aspect of the work. These contributions extend beyond the already documented reports and offer a framework which can be applied to other crops and regions which have been subjected to change due to climate and policies.

4 Conclusion

This study successfully applied Empirical Mode Decomposition (EMD) to deconstruct the non-stationary dynamics of agricultural yield in a semi-arid region. The analysis provides a new quantitative framework for diagnosing system resilience and forecasting productivity, with direct applications in water resources management, agricultural engineering, and regional infrastructure planning. Based on the results and discussion, the following principal conclusions are drawn:

1. System productivity is overwhelmingly governed by long-term, structural drivers rather than short-term climatic shocks. The EMD residual, representing the underlying trend, accounted for 94.5% of the total yield variance. This empirically quantifies the system's high inertia and path dependency, indicating that engineering and policy interventions must prioritize long-horizon strategies (e.g., sustainable water infrastructure, soil health management) over short-term shock mitigation to achieve lasting improvements in agricultural resilience.
2. The regional agricultural system has undergone a significant structural shift, with a productivity turning point identified post-2018. The EMD residual revealed a 25% decline from the peak trend, serving as a powerful, data-driven early warning of systemic stress. This diagnostic capability is critical for civil and environmental engineers in identifying emerging threats to regional carrying capacity, such as unsustainable groundwater abstraction or land degradation, before they escalate into systemic failure.
3. EMD provides a robust methodological framework for both diagnosing and forecasting complex agro-hydrological systems. The decomposition not only enhanced the interpretability of the yield dynamics by isolating the influence of ENSO-related teleconnections but also improved the predictive accuracy of a baseline ARIMA model by approximately 15–20%. This demonstrates the tangible value of EMD as a pre-processing tool for developing more reliable prognostic models essential for infrastructure planning, water allocation, and food security assessments Our research has identified a number of potential policies and management strategies that can be used to improve the resilience of dryland agro-ecosystems: (i) increasing soil carbon and organic matter via Conservation Agriculture; (ii) implementing long-term water infrastructure and sustainable irrigation practices; (iii) promoting crop diversity and use of crop diversity as a risk reduction strategy in response to systemic disturbances; and (iv) using Resilience Indices as diagnostic tools in the

design and implementation of agricultural development programs. Collectively, this provides a practical framework for developing the resilience of dryland agro-ecosystems.

The EMD-based framework for assessing crop resilience can apply beyond the scope of the pigeon pea and Adilabad district and therefore could also be applied to key crops like sorghum, cotton and maize as well as to semi-arid areas across India and worldwide. Therefore, this framework has a high level of scalability which makes it very useful for developing resilience plans for agriculture in a wide variety of agro-climatic zones. Adilabad district. The same methodology can be extended to other key crops such as sorghum, cotton, and maize, as well as to semi-arid regions across India and globally. This scalability underscores the utility of the framework for broad-based agricultural resilience planning in diverse agro-ecological contexts. Future research should be directed at validating these findings across a broader geographic area and integrating instrumental data, such as piezometric levels and soil moisture measurements, to mechanistically link the observed residual trend to specific physical drivers. Such work will further enhance the utility of this framework for the sustainable management of water and agricultural resources in complex, non-stationary environments

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6 Data Availability:

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

7 Declarations:

Conflict of interest: The authors declare no known competing interests.

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