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# Impact of climatic factors on the occurrence of malaria in hyper, high, moderate and low endemic States in India from 1995 to 2023

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## Abstract

**Background** Malaria has been surging in India for the past 3 years after reaching the recorded low in 2021. Among the possible reasons for this unexpected surge of cases, such as insufficient surveillance, slow and aggregated data reporting, endemic pockets in the tribal, dense forest areas where control programmes are difficult to reach, the role of climate change due to global warming has gained less attention. Similar to the diverse climatic conditions that prevail in different regions of India, the malaria distribution is also highly variable. Therefore, the impact of the annual average of climatic factors on the annual parasite index (API) in hyper-, high-, moderate-, and low-endemic states was analysed.

**Methods** The annual malaria data provided by the National Center for Vector Borne Diseases Control, and meteorological data provided by the India Meteorological Department, Pune, and Statista, were used to make temporal trend analysis, scatter plot analysis, clustered scatter plot analysis, and Spearman & Pearson correlation coefficient to determine the impact of climatic factors on the occurrence of malaria in hyper, high, moderate and low endemic States in India.

**Results** While the increasing annual temperature and rainfall negatively influenced the annual parasite index in high, moderate, and low endemic states, both had no influence on API in malaria hyperendemic states. Although minimum and maximum annual rainfall was found to be detrimental to the increase of API in low and moderate endemic states, moderate annual rainfall of high and hyperendemic states was favourable for increasing API. The increasing annual relative humidity negatively influenced the API in high and moderate endemic states and had a positive influence on the API in low endemic states. The humidity did not have any influence over the API in the hyperendemic state. Statistical analysis showed that, except in Mizoram, the annual mean temperature negatively influenced the API in all other states. The annual rainfall and average humidity were shown to be negatively associated with API only in Odisha.

**Conclusion** The present study revealed the relationships between annual climatic factors such as temperature, rainfall, and humidity with API in malaria hyper-, high-, moderate- and low endemic states in India.

**Keywords** Malaria, Climatic factors, Endemic, States, India, Impact

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## Background

Malaria continued to be one of the major public health problems in India after its reemergence in early 1976 [1] and is coming back again after going to the verge of elimination, as per the recent malaria situation report of the National Center for Vector Borne Diseases Control

(NCVBDC) [2]. Although such a comeback of malaria is not a new one, this time it gains more importance as the country is gearing up to deal with the last-mile challenges in the elimination of malaria by targeted 2030. The World Health Organization (WHO) estimated India's malaria burden to a mammoth figure of 3.3 million cases in 2022, leaving the country in first place in Southeast Asia [3]. While the annual average malaria cases in India have declined for the past 26 years from 2,926,197 in 1995 to 161,753 in 2021, the cases were surprisingly surging from 2022, with 8.37%, 28.92%, and 37.15% increase in 2022, 2023, and 2024, respectively [2] (Fig. 3D) compared with 2021 cases. As India is slated for malaria elimination by 2030 with its quest for a malaria-free country status [4], the recent surge in cases has created uncertainty in achieving this goal. This may extend the elimination target by a few more years. The possible factors responsible for the continued persistence of malaria in India and its recent surge despite tremendous efforts to eliminate it need to be explored. In addition to major challenges such as insufficient surveillance and slow and aggregated data reporting [5], the influence of climatic factors on the incidence of malaria has not received the required attention in India. Temperature is one of the main factors influencing both parasite growth and vector development, from egg hatching to various stages of larval and adult growth [6, 7].

Increased temperature could extend the window of malaria transmission, temporal distribution, and the man-hour density of vectors [8]. The relationship between rainfall and malaria transmission is intricate. On the one hand, rainfall increases standing water, which provides breeding habitats for vectors [9]; on the other hand, profuse rainfall may wash away the breeding waters and kill both larvae and adults [10]. With a high surface area to volume compared with other insects, mosquitoes are highly vulnerable to desiccation at low humidity levels [11]. Therefore, optimal temperature, rainfall, and relative humidity provide ample vector breeding sites and conducive conditions that determine vector activity and lifespan [12, 13].

Several mathematical and computer-based models have predicted that the number of people at risk of acquiring malaria in developing countries may increase by 5–15% due to climate change [14, 15]. Moreover, global warming may extend the boundaries of malaria to higher altitudes, and the duration of transmission may be shortened in southern states and widened in northern and eastern states of India [16]. Therefore, it is important to know how variations in annual climatic factors influence the annual incidence of malaria in regions with different endemicities that also fall into different climatic zones in India. The climatic conditions are extremely different in different regions of India, while some parts experiences temperate climate, others have either arid or tropical or mountain/polar-type climate [17]. Similarly, malaria distribution is also not uniform across the country [18]. Climate signals observed and recorded in India for more than 100 years show an increase in surface temperature by 0.7 °C between 1901 and 2018, a change in the spatial pattern of rainfall with respect to normal and occurrence of more intense and frequent extreme temperature, rainfall, and cyclone events [19]. Hence, there is a growing concern about the changing pattern of malaria over the years across India, which might be influenced by climatic factors.

The national strategic plan for malaria elimination 2023–27 has classified the malaria distribution in the country into four categories based on API (Annual Parasite Index), a key metric used to measure the prevalence of malaria in a given area, representing the number of confirmed malaria cases per 1000 people in a population over a year. API indicates the rate at which malaria parasites infect individuals within a community, i.e. a higher API denotes a higher level of malaria transmission in that region [20]. Different categories of endemicity are identified in India: category 0 (States with 0 incidence), category 1 (States with API $<$ 1 case/1000 population in all districts), category 2 (States with API $<$ 1 case/1000 population but some districts having API $\geq$ 1) and category 3 (States with API $\geq$ 1/1000 population). It recorded the movement of several States in its API Category from 3 to 0 during 2015–2022. For example, Puducherry and Lakshadweep moved from category 1 to 0; Andhra Pradesh, Assam, Bihar, Gujarat, Karnataka, Nagaland, Tamil Nadu, Telangana and Uttar Pradesh, from 2 to 1; Arunachal Pradesh and Dadra & Nagar Haveli, from 3 to 1; A & N Islands, Chhattisgarh, Jharkhand, Madhya Pradesh, Meghalaya and Odisha, from 3 to 1. Yet, a few states, such as Chandigarh, Daman & Diu, Delhi, Goa, Haryana, Himachal Pradesh, Jammu and Kashmir, Kerala, Manipur, Mizoram, Punjab, Rajasthan, Sikkim, Tripura, Maharashtra, Uttarakhand and West Bengal, find it difficult to move to low API category despite making tremendous efforts to control malaria. Among them, Mizoram and Tripura were the only two states still remained in the same category 3 [20].

The objective of this study was to investigate the long-term climatic changes in the annual incidence of malaria in some states, such as hyperendemic Mizoram, high endemic Odisha, moderate endemic Tamil Nadu, and low endemic Kerala, which are classified under temperate and dry winter, tropical savannah, tropical savannah, and steppe, and tropical rainforest, respectively [21]. The climatic factors conducive to the transmission of malaria in the hyperendemic area can be compared with the climatic factors of other categories of endemicity to determine the climatic conditions favourable for the transmission of the disease. Understanding the impact of climatic factors on malaria incidence is crucial for informing policymakers to frame effective policy recommendations. This understanding helps in designing targeted interventions, allocating resources efficiently, and adapting strategies to changing environmental conditions [8].

## Methods

The data on the annual incidence of malaria for the period 27 years, from 1995 to 2022, was collected from the health statistics of India, health information of India, and the National Health Profile, published by the Central Bureau of Health Intelligence [22] and the National Center for Vector Borne Diseases Control (NCVBDC), Ministry of Health & Family Welfare [2]. The meteorological data, such as the annual average maximum, minimum, and mean temperature and rainfall, were collected from the India Meteorological Department, Pune [23, 24], and Statista [25]. The data of annual average relative humidity was collected from Statista [25]. The annual malaria cases as API (annual parasite index) were compared with annual average mean temperature and rainfall for the period from 1995 to 2022 and annual relative humidity for the period from 2010 to 2022. Three different analyses were performed. In the first time-series analysis, the API vs. climatic factors, such as annual mean temperature, annual rainfall, and annual relative humidity were plotted separately for each State under study in the graph to see if the temporal trend of climatic factors had any visible association over the incidence of malaria. Year was taken in x-axis, API in y axis and climatic factors in y2 axis. A polynomial trendline with maximum $R^2$ value was drawn for API and each of the climatic factors for each State. In the second analysis, a scatter plot was drawn for each climatic factor Vs. API for each State under study with a linear trendline to determine their relationship. Further, a clustering scatter plot was also drawn for each climatic parameter under study for the data of all four States with API for the comparative analysis. To statistically measure the correlation between API and each of the climatic factors for each State, Spearman correlation analysis was done as it is better suited to analyse the non-linear relationship such as climatic variables vs. API [26]. In addition to that, the Pearson correlation coefficient (r) was also done as a comparison and P-values were calculated for both analyses. The annual incidence of malaria in India provided by NCVBDC [2] was used to determine the trend over the years from 1995 to 2024. A graph of the temporal trend of malaria cases in India was also drawn for a period from 29 years from 1995 to 2024 to highlight the recent surge of malaria cases.

## Results

### Temporal trend of various climatic factors and API

The combined temporal trend graph (Fig. 1), where the temporal trend of each climatic factor was combined with API, showed that the annual average mean temperature and rainfall increased over the study period from 1995 to 2022, with declining annual malaria cases in Odisha, Tamil Nadu, and Kerala. In contrast, the number of cases in Mizoram increased with fluctuating climatic factors. The annual average humidity increased in Odisha and Tamil Nadu and fluctuated in Kerala and Mizoram during the study period from 2010 to 2022.

### Scatter plot

In the scatter plot analysis (Fig. 2), while the trendline showed that the annual mean temperature had a negative relationship with API in Tamil Nadu, Odisha, and Kerala the same did not show any relationship in hyper-endemic Mizoram. While the trendline for API vs. rainfall showed a strong negative relationship in Odisha, it showed a weak negative relationship in both Tamil Nadu and Kerala. In contrast, the annual rainfall showed a very mild positive relationship with API in hyper-endemic Mizoram. The API vs humidity showed a negative relationship in Tamil Nadu and Odisha, Kerala showed a positive relationship, and Mizoram showed no relationship.

### Comparative scatter plot

Comparative scatter plot analysis (Fig. 3A–C) of all four states for each climatic factor under study showed that the annual mean temperature and annual rainfall played a substantial role in the transmission of malaria (Fig. 3A–C). In Tamil Nadu, the lowest annual mean temperature where cases were reported was 28 °C and the highest was 32.3 °C. In Kerala, the highest annual mean temperature at which malaria cases were reported was 27.8 °C and the lowest was 23.25 °C (Fig. 3A). The clustering pattern in both states showed that the cases were minimal when the temperature was the highest despite the highest mean temperature, whereas cases reported in Kerala were lower than the lowest mean temperature of Tamil Nadu. In hyper-endemic Mizoram and high-endemic Odisha, the clustering of API in response to temperature did not show any specific pattern, except for the temperature range where cases were reported, which was the lowest among all four states. The clustering of the API in response to the annual mean rainfall showed that, in Tamil Nadu, the API with the highest annual mean rainfall was (1382 mm) much lower than the API with the lowest rainfall (1871 mm) in Kerala. However, even the


**Fig. 1** Temporal trend of various climatic factors and API with $R^2$ values in the study states during the study period 1995–2022 for temperature and rainfall and 2010–2022 for relative humidity

lowest rainfall (377 mm) in Tamil Nadu and the highest rainfall (3606 mm) in Kerala had an incidence of malaria. In contrast, the high endemic Odisha and hyperendemic Mizoram showed API corresponding to moderate rainfall of 1059–1716 mm and 989–2246 mm, respectively. The clustering pattern shows that the lowest API in Kerala and Tamil Nadu corresponds to the highest rainfall in both states compared with Mizoram and Odisha, where the highest API was related to moderate rainfall (Fig. 3B). The clustering pattern of the API with the corresponding humidity (Fig. 3C) reveals that the range of humidity was very wide (75.03 to 98) in hyperendemic Mizoram in contrast with Tamil Nadu (58.09–69.5), Kerala (77.25–81.42) and Odisha (58.78–79.75).

### Temporal trend of malaria in India

Analysis of the temporal trend of malaria shows that the number of cases has been increasing for the past three consecutive years after 2021 (Fig. 3D).

### Spearman and Pearson correlation analysis

The Spearman (rs) and Pearson correlation (r) (Table 1) for annual mean temperature vs. API were −0.75 & −0.40 for Kerala, showing a strong negative association followed by −0.70 & −0.63 for Tamil Nadu and −0.57 & −0.61 for Odisha. In hyper-endemic Mizoram, the Spearman and Pearson coefficients of −0.01 & −0.02, showed that the change in annual temperature did not influence the API. Similarly, Spearman and Pearson values of 0.06 & 0.04 and −0.25 & −0.01 show that the annual rainfall and annual relative humidity did not influence the trend of API in Mizoram. While the annual average humidity, with the Spearman coefficient value of −0.60 showed a strong negative relationship with API in Odisha, the Pearson coefficient value of −0.51 showed a negative influence of annual rainfall on the trend of API. For the rest of the analysis such as annual rainfall and humidity vs. API in Tamil Nadu and Kerala, both Spearman and Pearson correlation coefficients were not statistically significant, showing the absence of clear influence of those climatic factors over API.

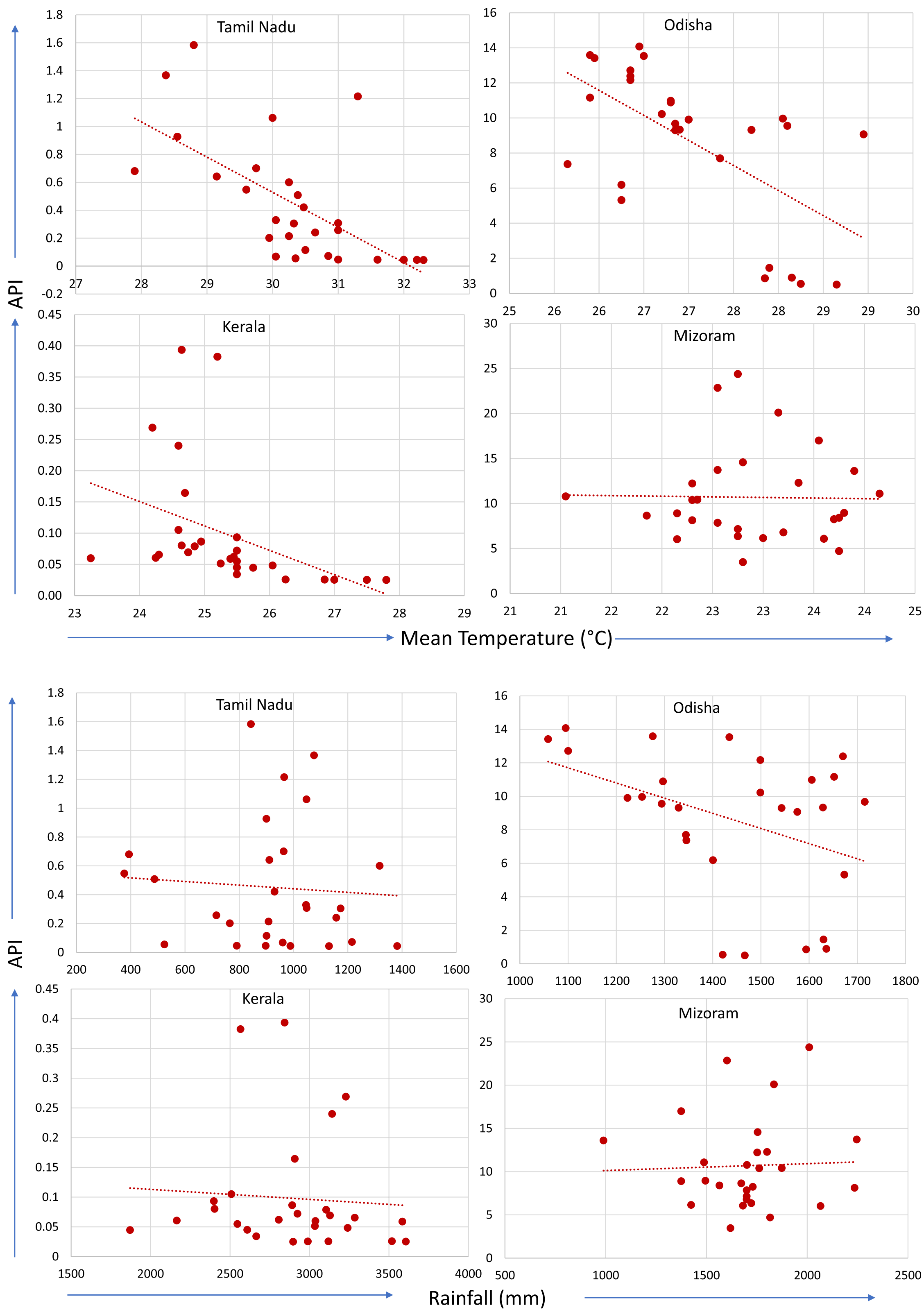


**Fig. 2** Relationship of annual parasitic index (API) with climatic factors such as mean temperature, rainfall and humidity in different study States such as Tamil Nadu, Kerala, Odisha and Mizoram

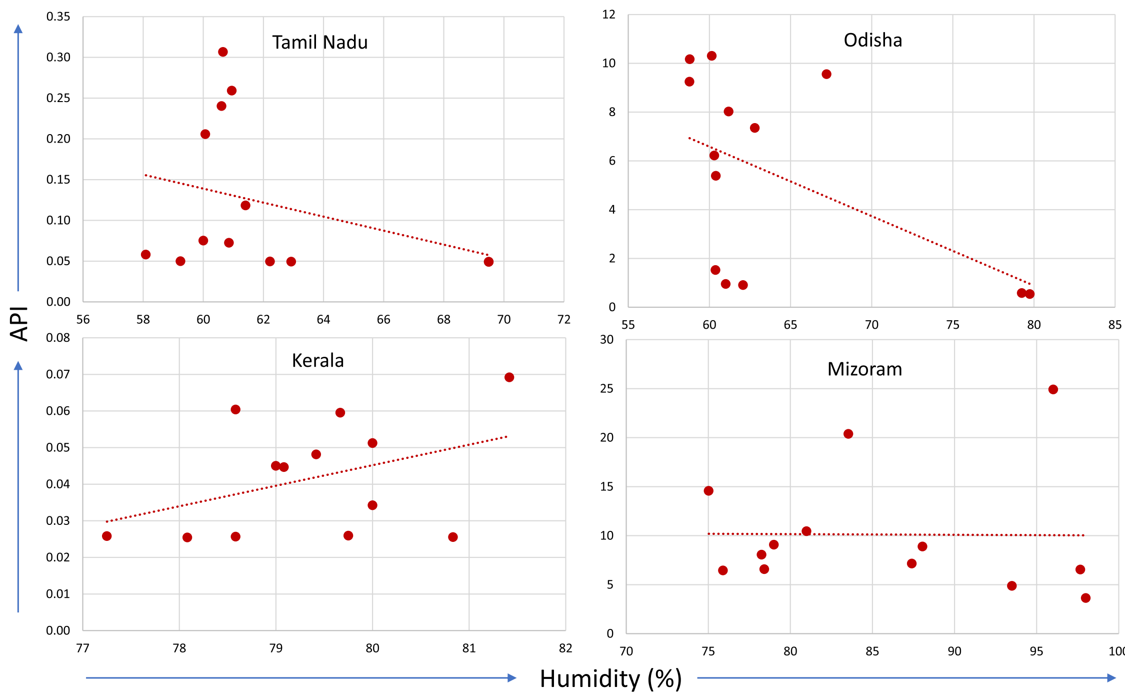


**Fig. 2** continued

The data of the annual climatic variables with the corresponding API for each state are given in Table 2 for comparison.

## Discussion

This is the first study to estimate the association of annual average temperature, rainfall from 1995 to 2023, and relative humidity from 2010 to 2022 with malaria incidence in four states with different malaria endemicities and climatic conditions, thereby providing a comprehensive overview of the impact of temperature, rainfall, and humidity on the incidence of malaria in India. This study provides valuable insights into the relationship between climatic factors and the incidence of malaria. Although the temporal trend of climatic factors with the temporal trend of API showed a particular trend for each, it only gave a superficial association of API and climatic factors, such as increasing annual mean temperature, fluctuating annual rainfall in all the states, increasing and fluctuating humidity in Tamil Nadu, Odisha and Mizoram, and Kerala, respectively, and decreased malaria in States other than Mizoram. However, scatter plot analysis, which was performed to determine the relationship between API and climatic factors, clearly defined the association of each climatic factor with API. Even though the annual average temperature range was highly different in the States of Tamil Nadu, Kerala, and Odisha, the trendline showed that the API had a negative association with the temperature increase in all states except Mizoram. One possible reason for this might be that the increase in annual average temperature was within the optimal breeding range of *Anopheles culicifacies* [27], the main vector of malaria in Mizoram [28]; hence, increasing the temperature did not have any influence on the incidence of malaria. In contrast, API was negatively influenced by the temperature increase in other study States, such as Tamil Nadu, Kerala, and Odisha. This is possible because the normal temperature range was higher in these states than in Mizoram. These results are consistent with those of Minakawa et al. [29], which showed that temperature plays a crucial role in API by selecting the vector species of malaria such as *Anopheles gambiae* and *Anopheles arabiensis* in Kenya. A study in China reported that a 5 °C increase in average temperature above 10 °C was associated with a 22% increase in malaria cases [30]. Increasing the annual temperature in European countries with temperate climates has increased the number of malaria transmission sessions [31]. However, increasing annual average temperature in tropical countries, such as Ghana and Nigeria, was found to have a negative impact on API [32]. These results are in line with those findings that in the temperate climate Mizoram, the temperature did not have any negative influence on the API, whereas in the other states with tropical climates, the temperature negatively influenced the API. In general, the malaria transmission window in relation to temperature is between

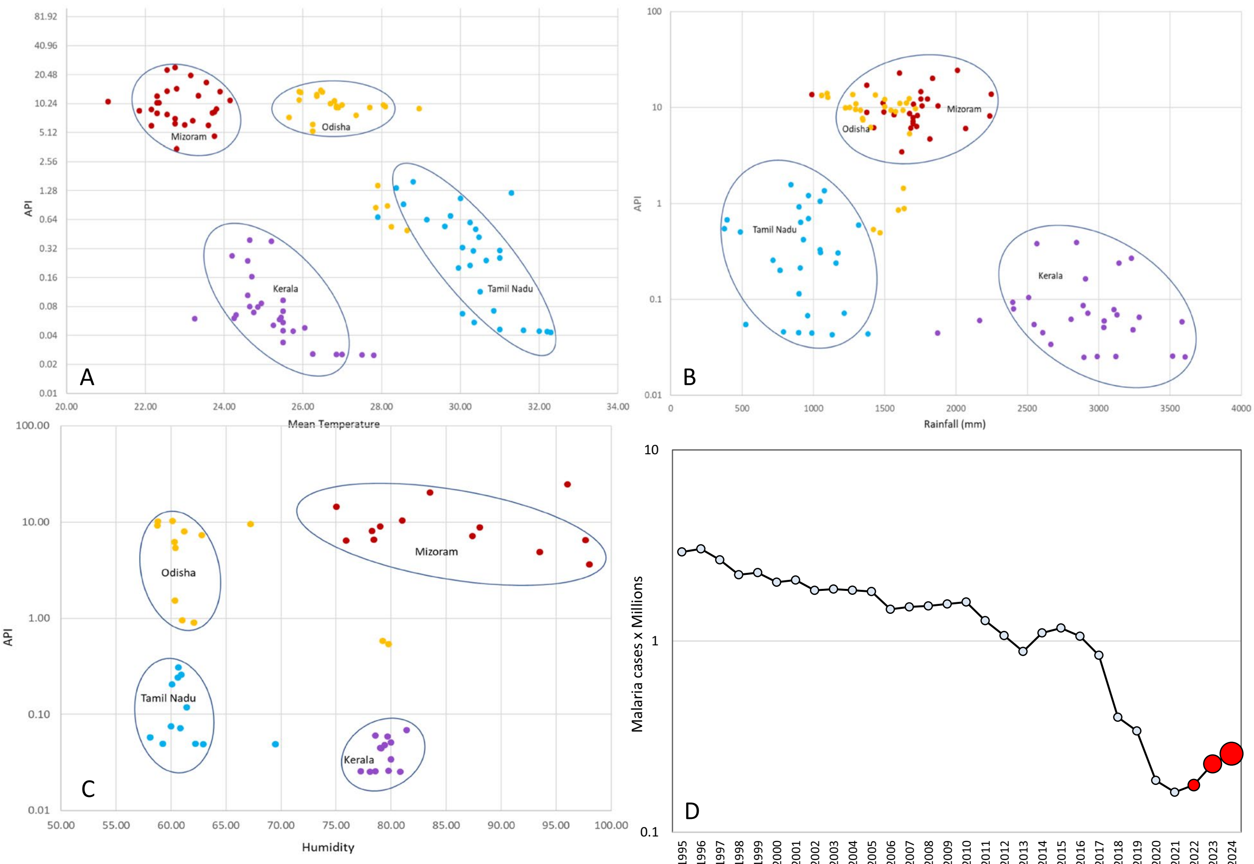


**Fig. 3** Comparative analysis of climatic parameters, mean temperature (**A**), rainfall (**B**) and humidity (**C**) in hyper (Mizoram), high (Odisha), moderate (Tamil Nadu) and low (Kerala) malaria endemic States under study. **D** Increasing trend of malaria after 2021

**Table 1** Relationship of climatic factors over the temporal trend of API in the respective study States

| State | Annual Mean Temperature | | | | Annual Rainfall | | | | Annual Average Humidity | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Pearson coefficient (r) | | Spearman coefficient ($r_s$) | | Pearson coefficient (r) | | Spearman coefficient ($r_s$) | | Pearson coefficient (r) | | Spearman coefficient ($r_s$) | |
| Mizoram—hyper endemic | − 0.02 | P > 0.05 | − 0.01 | P > 0.05 | 0.04 | P > 0.05 | 0.06 | P > 0.05 | − 0.01 | P > 0.05 | **− 0.25** | P > 0.05 |
| Odisha—high endemic | **− 0.61** | P < 0.01 | **− 0.57** | P < 0.01 | **− 0.41** | P < 0.05 | **− 0.37** | P > 0.05 | **− 0.51** | P > 0.05 | **− 0.60** | P < 0.05 |
| Tamil Nadu—moderate endemic | **− 0.63** | P < 0.01 | **− 0.70** | P < 0.01 | − 0.07 | P > 0.05 | **− 0.11** | P > 0.05 | **− 0.32** | P > 0.05 | **− 0.36** | P > 0.05 |
| Kerala—low endemic | **− 0.40** | P < 0.05 | **− 0.75** | P < 0.01 | − 0.05 | P > 0.05 | **− 0.15** | P > 0.05 | **0.38** | P > 0.05 | **0.24** | P > 0.05 |

No statistically significant influence of climatic factors on API.

Negative influence of climatic factors on API.

Statistically non-significant influence of climatic factors on API.

**Table 2** Annual climactic variables with corresponding API of the study States

| | Mizoram | | | | Odisha | | | | Tamil Nadu | | | | Kerala | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean temp. (°C) | Annual rainfall (cm) | Average humidity (%) | API | Mean temp. (°C) | Annual rainfall (cm) | Average humidity (%) | API | Mean temp. (°C) | Annual rainfall (cm) | Average humidity (%) | API | Mean temp. (°C) | Annual rainfall (cm) | Annual humidity (%) | API |
| 1995 | 22.55 | 160.2 | | 22.84 | 26.80 | 160.57 | | 10.98 | 28.80 | 84.31 | | 1.58 | 24.65 | 284.35 | | 0.39 |
| 1996 | 22.55 | 224.6 | | 13.72 | 25.95 | 105.86 | | 13.41 | 28.38 | 107.57 | | 1.37 | 25.20 | 256.61 | | 0.38 |
| 1997 | 23.90 | 98.9 | | 13.60 | 26.35 | 149.9 | | 12.16 | 31.30 | 96.57 | | 1.21 | 24.20 | 322.89 | | 0.27 |
| 1998 | 22.30 | 175.2 | | 12.21 | 25.90 | 127.58 | | 13.58 | 30.00 | 104.8 | | 1.06 | 24.60 | 314.24 | | 0.24 |
| 1999 | 23.55 | 137.5 | | 16.99 | 26.50 | 143.47 | | 13.53 | 28.55 | 90.03 | | 0.93 | 24.70 | 290.75 | | 0.16 |
| 2000 | 22.35 | 187.4 | | 10.41 | 26.45 | 109.52 | | 14.07 | 29.75 | 96.37 | | 0.70 | 25.50 | 239.84 | | 0.09 |
| 2001 | 23.35 | 180.1 | | 12.28 | 26.35 | 167.03 | | 12.38 | 30.39 | 48.79 | | 0.51 | 25.50 | 292.44 | | 0.07 |
| 2002 | 21.85 | 167.3 | | 8.64 | 26.35 | 110.03 | | 12.71 | 29.60 | 37.66 | | 0.55 | 24.60 | 250.87 | | 0.11 |
| 2003 | 22.55 | 170 | | 7.84 | 25.90 | 165.2 | | 11.16 | 27.90 | 39.39 | | 0.68 | 24.65 | 240.28 | | 0.08 |
| 2004 | 23.70 | 173 | | 8.24 | 26.80 | 129.7 | | 10.89 | 29.15 | 91.12 | | 0.64 | 24.95 | 289.12 | | 0.09 |
| 2005 | 24.15 | 148.8 | | 11.07 | 26.70 | 149.9 | | 10.22 | 30.25 | 131.74 | | 0.60 | 24.85 | 310.51 | | 0.08 |
| 2006 | 21.05 | 170.1 | | 10.77 | 26.85 | 171.56 | | 9.67 | 30.48 | 93.02 | | 0.42 | 24.30 | 328.5 | | 0.07 |
| 2007 | 22.15 | 206.6 | | 6.02 | 26.90 | 162.89 | | 9.33 | 30.05 | 104.63 | | 0.33 | 25.40 | 358.48 | | 0.06 |
| 2008 | 22.75 | 170 | | 7.14 | 26.85 | 154.31 | | 9.30 | 30.33 | 117.35 | | 0.30 | 25.50 | 254.65 | | 0.05 |
| 2009 | 23.80 | 149.5 | | 8.95 | 27.70 | 132.94 | | 9.31 | 30.25 | 90.82 | | 0.21 | 25.45 | 280.67 | | 0.06 |
| 2010 | 22.80 | 175.4 | 75.03 | 14.57 | 28.10 | 129.43 | 67.22 | 9.55 | 30.65 | 115.76 | 60.61 | 0.24 | 24.75 | 312.91 | 81.42 | 0.07 |
| 2011 | 22.30 | 223.5 | 78.25 | 8.06 | 25.65 | 134.56 | 62.80 | 7.35 | 31.00 | 104.85 | 60.66 | 0.31 | 23.25 | 303.73 | 79.67 | 0.06 |
| 2012 | 22.15 | 137.5 | 88.05 | 8.89 | 26.25 | 140.07 | 60.31 | 6.22 | 31.00 | 71.59 | 60.95 | 0.26 | 24.25 | 216.48 | 78.58 | 0.06 |
| 2013 | 22.30 | 176.2 | 80.99 | 10.45 | 26.25 | 167.32 | 60.40 | 5.38 | 29.95 | 76.55 | 60.07 | 0.21 | 26.05 | 324.06 | 79.42 | 0.05 |
| 2014 | 23.15 | 183.5 | 83.54 | 20.37 | 28.95 | 157.57 | 58.78 | 9.24 | 30.50 | 90.07 | 61.41 | 0.12 | 25.25 | 303.42 | 80.00 | 0.05 |
| 2015 | 22.75 | 201 | 96.02 | 24.91 | 27.00 | 122.34 | 58.80 | 10.17 | 30.85 | 121.55 | 60.00 | 0.08 | 25.50 | 260.83 | 79.00 | 0.05 |
| 2016 | 22.75 | 172.3 | 97.67 | 6.54 | 28.05 | 125.35 | 60.15 | 10.30 | 30.35 | 52.44 | 58.09 | 0.06 | 25.75 | 187.09 | 79.08 | 0.04 |
| 2017 | 23.75 | 181.6 | 93.50 | 4.88 | 27.35 | 134.45 | 61.19 | 8.02 | 30.05 | 96.04 | 60.86 | 0.07 | 25.50 | 266.49 | 80.00 | 0.03 |
| 2018 | 22.80 | 201.1 | 98.00 | 3.63 | 27.92 | 163 | 60.38 | 1.52 | 31.00 | 79.1 | 59.24 | 0.05 | 26.25 | 351.9 | 79.75 | 0.03 |
| 2019 | 23.20 | 210.4 | 87.40 | 7.15 | 30.00 | 159.4 | 62.08 | 0.90 | 31.60 | 89.76 | 62.22 | 0.05 | 26.85 | 311.92 | 77.25 | 0.03 |
| 2020 | 23.20 | 240.4 | 75.90 | 6.45 | 30.25 | 163.59 | 61.01 | 0.95 | 31.00 | 98.85 | 62.93 | 0.05 | 27.00 | 298.98 | 78.58 | 0.03 |
| 2021 | 23.60 | 142.4 | 78.42 | 6.58 | 30.65 | 142.09 | 79.25 | 0.58 | 31.40 | 138.22 | 69.50 | 0.05 | 27.40 | 360.64 | 80.83 | 0.03 |
| 2022 | 23.80 | 156.46 | 79.00 | 9.07 | 30.85 | 146.67 | 79.75 | 0.54 | 31.60 | 113.1 | 69.50 | 0.05 | 27.60 | 289.7 | 78.08 | 0.03 |

15 and 40 °C, and the number of days required for a vector to complete its cycle varies according to the number of days favourable temperature persists with optimal humidity. For example, the vector of *P. vivax* requires 15–25 days if the temperature persists at 15–25 °C, but requires only 6–10 days to complete the life cycle if the temperature range remains within 25–30 °C [16]. The results further demonstrate that the relationship between API and annual rainfall was strongly negative for Odisha and weakly negative for Tamil Nadu and Kerala, showing a very weak positive association (though not statistically significant). It shows that the increasing rainfall might have washed away the existing vector breeding sites in Odisha and to some extent in Tamil Nadu and Kerala, it slightly increased vector breeding habitats in Mizoram. While profuse rainfall affects some *Anopheles* species, others are unaffected. For example, *Anopheles fluviatilis*, the main vector of malaria in Odisha [28], breeds largely in slow-moving water bodies such as streams, irrigation channels, and stream pools [33], and increasing rainfall has a negative impact, as heavy rainfall can easily remove immatures from such breeding habitats. However, rainfall did not have any effect on the incidence of malaria in other study States, such as Tamil Nadu, Kerala, and Mizoram. This is possibly because, in highly urbanized States, such as Tamil Nadu and Kerala, the main vectors of malaria transmission are Anopheles stephensi [28], which breeds mainly in overhead tanks, wells, construction sites, roof gutters, underground tanks, and curing pits that are not easily disturbed by increasing rainfall [34]. In Mizoram, the main vector is *An. culicifacies* [28] that can breed a wide variety of habitats that are less affected by heavy rainfall. Similarly, humidity also did not play any role in Mizoram's hyper-endemic state, while the same favoured malaria in Kerala and negatively influenced Tamil Nadu and Odisha.

The all-state combined clustering scatter plot for temperature showed that increasing API was associated with reduced annual temperature, and vice versa, in Tamil Nadu and Kerala. However, no such association was observed between API and annual mean temperature in Odisha and Mizoram. Similarly, moderate annual rainfall in Odisha and Mizoram resulted in increased API, whereas the reduced annual rainfall in Tamil Nadu and increased annual rainfall in Kerala resulted in decreased API. While Mizoram showed a peculiar pattern of a wide range in annual average humidity, the other states showed that API fell within a short range of humidity. All other States showed either no correlation or a negative correlation of varying degrees between API and climatic factors, except Kerala, which showed a positive association between humidity and API. The clustering scatter plot showed that Tamil Nadu and Kerala have different minimum annual temperatures that favour API, and maximum annual temperatures that do not favour API. It also showed that while moderate rainfall was related to higher API, the lower and higher annual rainfall, as in Tamil Nadu and Kerala, was detrimental to API. The clustering pattern of the API association with climatic factors showed that while temperature played a major role in the southern Indian States of Tamil Nadu and Kerala, rainfall played a major role in the prevalence of malaria in all three states. The humidity did not play any significant role as the low endemic Kerala and hyper endemic Mizoram shared the same humidity range similar to the low endemic Tamil Nadu and high endemic Odisha.

The flat trendline of malaria hyper-endemic Mizoram for the tested climatic factors showed that they did not play any role in its malaria hyper-endemicity. This unique picture of the non-association between climatic factors and API in Mizoram suggests the involvement of other factors that need to be focused on. Even though the malaria control programme is executed at the national level, there might be some areas that require more attention. For example, the highest API in the western and eastern districts of Mizoram shares porous international borders with Bangladesh and Myanmar, countries that are endemic for malaria [35]. The people in the bordering district of Mizoram have historical and ethnic ties with the people of Myanmar and Bangladesh and interact through the porous border, which may increase the chances of acquiring malaria from neighbouring countries [36]. Other factors, such as the domination of tribals (~94%) [37] living in dense forest cover (89% of the state) with inaccessible areas, make malaria control efforts difficult to reach [38] in States such as Mizoram and Odisha. In contrast, in highly urbanized States such as Tamil Nadu and Kerala, the reach of malaria control programs was maximum and played a vital role in limiting the incidence of malaria, in addition to the climatic factors discussed. The negative association of temperature with API in major States such as Tamil Nadu, Kerala, and Odisha shows that global warming may change the boundaries and push malaria endemicity from the hotter peninsular region to cooler northern regions, as predicted for Africa [38]. However, each State had a temperature range that facilitated malaria transmission that was different from the others. The Spearman correlation was found to be better in determining the influence of climatic factors on the API than the Pearson correlation.

Among the two main malaria parasite species, *P. falciparum* and *P. vivax*, the former has received more attention because it is known to cause higher mortality than the latter in India [39]. However, *P. vivax* is recently known to cause 1.47 to 6% relapse [40] due to its dormant liver stage (the hypnozoites) [39]. In general, the parasite species in the tropical region mostly exhibit shorter relapse intervals of 3–5 weeks; those found in temperate and subtropical areas exhibit longer dormant periods of 8–10 months or even longer, between the occurrence of primary infection and its relapse [41]. Although temperature affects the two parasite species differently in mosquito vectors [42], the effect of climatic factors, including temperature, on the success of parasite species has not yet been determined. While the hyperendemic Mizoram and high-endemic Odisha were mainly affected by *P. falciparum* malaria, the moderate and low endemic States, Tamil Nadu and Kerala, were affected by *P. vivax* malaria [40], and their association with climatic variables is yet to be ascertained. Previous studies conducted in China [43, 44] also did not provide any evidence of different influence of climate in different species.

The feasibility of accurate forecasts of malaria based on climatic variables has recently been demonstrated [11], and our study provides baseline data for devising a climate-based early warning system to predict impending outbreaks. Integrating climate data into malaria surveillance systems to anticipate and respond to changes in transmission patterns, implementing climate-resilient measures, such as improved drainage systems and flood control measures, and designing intervention methods to synchronize with climatic predictions can help reduce vector breeding and malaria transmission.

This study has some limitations. First, data from government health facilities were used, which may be incomplete as many private health agencies, hospitals, diagnostic laboratories, and medical practitioners either do not or partially report cases. Although underreporting of diseases is a major problem in India [45], the number of cases reported each year may represent a fairly stable proportion of cases that actually occurred, which may provide an idea about the temporal trend of a particular disease [46]. Second, this ecological study was based on linked aggregated data on malaria incidence and meteorological data, which might have caused ecological fallacies. Third, as annual data was used in this study, the lag time pattern was not considered, which generally cannot be overlooked for this type of study. However, a few recent studies have successfully used annual climatic variable data to correlate their relationship with API [8, 11, 47] to determine the influence of climatic factors on malaria incidence.

## Conclusions

The present study revealed the relationships between API and climate factors. Although higher temperatures had a negative relationship with the API in Odisha, Tamil Nadu, and Kerala, the temperature range that affected the API was unique for each state. Climatic factors, such as temperature, rainfall, and humidity, did not show any significant association with API in malaria-hyperendemic Mizoram. Only in the moderate endemic Odisha, the rainfall and humidity were significantly negatively associated with API. In the remaining two states, Tamil Nadu and Kerala, rainfall and humidity did not significantly affect API. It was concluded that temperature negatively influenced API in states with a tropical climate, and other factors such as tribal population ratio, forest cover, international porous border, and implementation of malaria eradication programmes determined API in states such as Mizoram with a temperate climate.

### Abbreviations

| | |
|---|---|
| API | Annual Parasite Index |
| NCVBDC | National Center for Vector Borne Diseases Control |
| WHO | World Health Organization |

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### Author contributions

M.M: conceived the concept, conceptualized, planned the study, and wrote the manuscript, R.P, and R.V: did collection and analysis of data, P.R: verified and corrected the manuscript.

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### Availability of data and materials

No datasets were generated or analysed during the current study.

## Declarations

### Ethics approval and consent to participate

Not applicable.

### Consent for publication

Not applicable.

### Competing interests

The authors declare no competing interests.

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